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The trust of consumers in the emerging world of Smart Machines/AI

The issue of Transparency

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The trust of consumers in the emerging world of Smart Machines/AI: The issue of Transparency

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Abstract

As Artificial Intelligence (AI) is becoming more and more present in our society, it is then very important to focus on the different drivers of AI consumption. As a quite new technology, we find a certain reluctance towards AI for multiple reasons, such as misunderstanding the technology and everything that is implied by it. In this work, we will focus on users' perceived transparency. Indeed, a regularly given argument is the lack of transparency as AI is often referred to as a black box. Nevertheless, some methods are currently developed to make AI more interpretable and thus explainable. Our goal here will be to determine the impact of perceived transparency on users' trust and their intention to use AI. To do so, we performed quantitative analysis on 142 respondents. It came out that perceived transparency has an impact on users' trust, such as users' trust has an impact on their intention to use AI. We also find out that the profession and revenue can influence the relationship between users' trust and their intention to use AI. Nevertheless, AI Education had no impact on our work, and could probably be more studied in future research.

Keywords: Artificial Intelligence, Transparency, Trust, Intention to Use, Interpretability

Preface

This thesis represents the culmination of my 5 years in management engineering at the University of Namur. I would like to thank all the people who have, in one way or another, helped, advised, or motivated me during the realization of this one.

I would first like to thank my thesis promotor, Prof. Wafa Hammedi, for the time spent guiding me, motivating me, and advancing my thinking throughout this work. Without her and her valuable advice, I would never have been able to complete this thesis.

I also want to thank the Data Science team from the BIL (Bank in Luxembourg) for the internship they proposed to me. I am grateful for their contributions of knowledges and advice with the topic of my thesis.

Then, I would like to thank all the participants who were kind enough to take the time to participate in my survey posted on social media. These answers form the basis of the analyses carried out and therefore contribute greatly to the realization of this work.

Finally, I would like to thank all the people who, from near or far, have helped me or supported me, at some point, during my thesis. I am particularly thinking of my family who never stopped believing in me throughout my studies as well as my friends on whom I can always count and my girlfriend, Diane.

To *Jack*

Summary Table

Chapter 1: Introduction

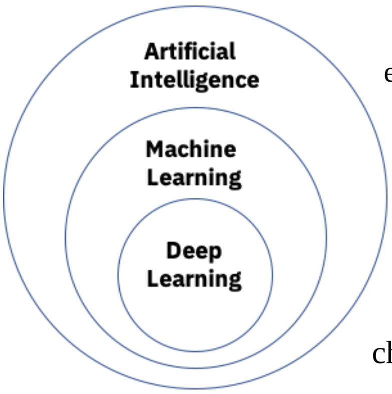
1.1. Context

AI and Smart Machines becomes more and more present in our society, proposing a vision with huge perspectives. AI, as defined by the European Commission report of 2018, refers to "*machines or agents that are capable of observing their environment, learning, and based on the knowledge and experience gained, taking intelligent action or proposing decisions*", or also "*the art of creating machines that perform functions that require intelligence when performed by people*" (Kurzweil – 1992)

We find the origin of AI in the 40-50s (even the early 60's), with a logic-based approach mainly initiated by Alan Turing who was interested in the mathematical possibilities of AI (Rockwell - 2017). AI then slowly moved towards knowledge-based expert systems in the 70s and 80s, with mechanical reasoning based on knowledge, making AI specialized in a specific domain. This system very often includes conditional rules, namely IF-THEN rules (European Commission report - 2018). In 2020, data-driven approaches have emerged, and these approaches are important as the volume of data generated is increasing every day with 90% of the data in the world that has been created in the last 2 years (Dilmegani, 2021), allowing a new discovery process thanks to the technology by identifying factors that are unseen or invisible to the human eye (Haney, 2020).

Robots are already common in our daily lives, and we can expect exponential growth in the years to come. AI brings the perspective in which Smart Machines and robots are predicted to bring a deep impact on the service sector as we can observe a growing interest towards these machines (Lu, Wirtz, Kunz, Paluch, Gruber, Martins & Patterson – 2020). AI brings to robotics a lot of opportunities in terms of innovations that have the power to change service industries, changing the service at multiple levels from the micro service to the macro service (Wirtz, Patterson, Kunz, Lu, Paluch & Martins – 2018). Those machines bring a social presence, where humanoid robots can replace frontline service employees or even collaborate with employees to deliver customer service (Van Doorn, Mende, Noble, Hulland, Ostrom, Grewal & Petersen – 2017). The impact of the robots is crucial: the characteristics of the Smart Machines (for instance the perceived warmth, the competence, the attractiveness) and the consumer properties (for instance the relationship orientation, technological readiness and anthropomorphizing of the smart machines) will determine customers' service outcomes, such as satisfaction, loyalty and well-being service (Van Doorn et al., 2017). In addition, if consumers are comfortable with robotic interactions, human-like appearance of robots is more important than social functioning features. At the opposite, if consumers are uncomfortable with robotic interactions, social functioning of robots is more important than their human-like appearance (van Pinxteren, Wetzels,* Rüger, Pluymaekers & Wetzels – 2019).

Figure 1 Sections of AI



The field of **AI** is a universe of computer technology that will introduce everything remotely resembling human intelligence (IBM – 2021). Smarts Machines are a layer above AI in the sense that Smarts Machines are technologies with embedded AI, capable of adapting to the situation. AI is therefore composed of certain sub-categories that are often linked to each other.

We find **Machine Learning** as a subcategory of AI that has the characteristic of learning, automatically reprogramming itself according to the data it digests, allowing it to be efficient in a specific task for which it was designed (IBM – 2021). We find different categories such as *supervised learning* and *unsupervised learning*. The supervised learning is explicitly used for classification or predictions. In this type of learning, we want to map input to output with labels that are known. It exists multiple algorithms that help us to achieve our classification/prediction goals with for instance Logistic Regression, Naïve Bayes, Support Vector Machines, Neural Networks, … (Soni – 2021). In other terms, we develop predictive models based on both input and output data. At the opposite, we find the unsupervised learning who is mainly used for clustering or anomaly detection. This type of learning help is to learn the inherent structure of the data without using explicitly provided labels (Soni – 2021). In other terms, we group and interpret data based only on input data.

Figure 3 Schematic view of Unsupervised Learning

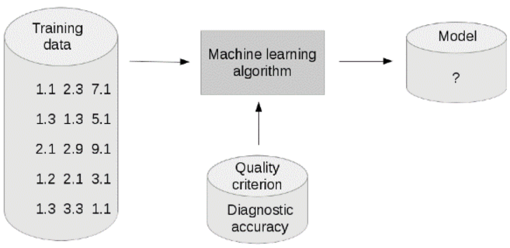
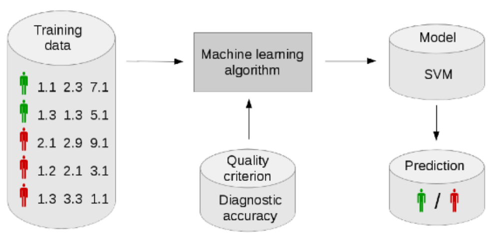
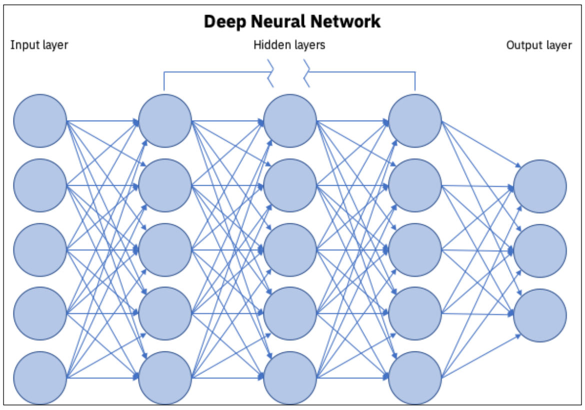


Figure 2 Schematic view of Supervised Learning



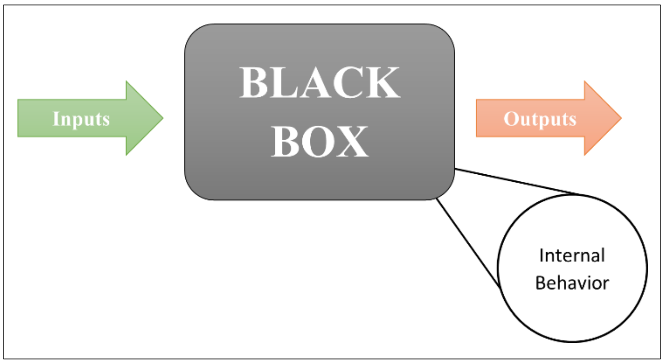
We also find **Deep Learning** models based on deep neural networks. They are mainly used with supervised learning models but are still capable of working with unsupervised learning models. The deep learning is used in sophisticated applications requiring for instance image recognition systems, identifying everyday objects more quickly and accurately than humans (IBM – 2021).

Figure 4 Schematic view of a Neural Network (Deep Learning model)



Nevertheless, a significant concern about AI is the complexity that lies behind these mechanisms, often requiring a choice between understanding the human and the complexity in which the model immerses itself. Therefore, it is essential to find the in-between with respect to the complexity and the model interpretability (Frenay – 2019). This complexity is often perceived as a black box in which we do not see the mechanisms that process the inputs, thus producing outputs that are difficult to understand (Kaplan & Haenlein, 2020). Within this black box we can find the internal behaviour of the model. From this idea of a black box comes certain issues concerning the understanding of AI, both in terms of perception and comprehension, often leading to a distrust of AI, the main reason being a lack of knowledge about the subject.

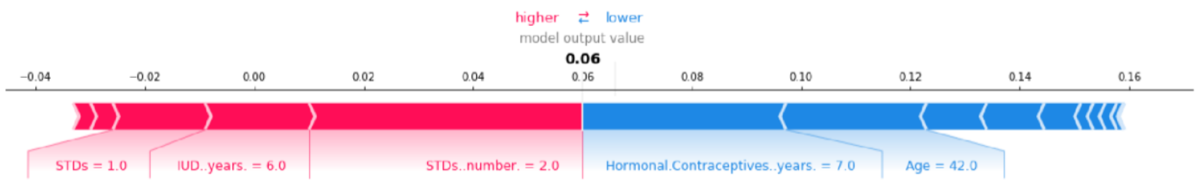
Figure 5 The process of AI and the black box



About Smart Machines, a study suggests that users have positive and approving attitudes towards Smart Machines when they had real exposure to those machines. Also, when the Smart Machines were hypothetical, research participants predominantly showed negative and ambivalent attitudes (Savela, Turja and Oksanen, 2018). This helps to understand that besides the problem of transparency, there is also an apprehension of the unknown that is relieved by contact with this technology. However, this problem of perception remains from a consumer's point of view. From a business perspective, the question of perception is widely taken seriously lines in the world of data science. In this area, there is a huge need to interpret data as data scientists are often confronted with the business side of an organization (who do not necessarily have the knowledge to understand or even interpret the results of analyses via machine learning for instance); it is therefore important to provide a way to better interpret the model and why it leads to one or another result.

In the business area, some methods have been developed to deal with this problem of interpretability and the best known of them is called SHAP. This method is based on the Shapley Values, coming from game theory in which each feature value is considered as a player, where we find the prediction as the payoff, and Shapley values help us to determine how to allocate this payoff between features. SHAP is built on the Shapley Values, providing an aggregation that allows a better understanding at the aggregate and individual level of the decision(s), with graphs that provide insight into the most important feature, and its associated value.

Figure 6 Example of Individual Interpretation (SHAP)



On the image above, the red features give an impact pushing the decision on the right (and so, leading to positive predictions), where the blue ones do the opposite, in an individual way.

The method SHAP is powerful because this method allows us to express what the model does, but it also helps to refine the model with a better understanding about the reasons we have false positive results. Moreover, interpretability methods such as SHAP are powerful within a company, in the case where each decision must be analysed before being validated and must therefore be well understood by all decision makers. In this business case, timing is important, but the different parties take the time to understand and apply the decision.

In opposition, in the consumer-oriented aspect, the objective is to convince quickly, and in this case, to reassure about the technology used. Interpretability techniques remain interesting but will only touch the most curious, but it remains important to understand that one can interpret a decision and then explain almost all decisions made by AI. Consumers are still mixed about AI, and rightly so: the use of AI is still new in our daily consumption involving technology, and fear of the unknown is setting in as with the arrival of the internet or any other new technology. According to a Pega study, consumers are still uncomfortable with AI, but especially non-AI users: the latter are 36% uncomfortable to 19% of AI users, while 25% are comfortable for non-AI users and 55% for AI users, more than double. In addition, 88% of consumers demand more transparency on how and when to deploy Smart Machines. As the use of these machines becomes more prevalent, it is therefore especially important to understand what will create consumer trust in these new technologies we will live with, and to do so, we will focus on the transparency of AI as the driver of consumer trust and perception. Transparency is an issue that is often highlighted in the literature and understanding consumer confidence in using these new tools is key to increasing their trust and thus increasing their usage. Moreover, as we have seen previously, the comfort of use tends to increase when they had direct contact with the Smart Machines in question, whether they are already AI users or not.

Therefore, the consumer's trust in AI is important, especially in terms of transparency. The power given to the machine (in terms of planning or giving advice for a decision) can impair the trust given by consumers. "Why have I been placed in this category?" or another example "why am I considered as a risky consumer?"(in the banking sector which also uses machine learning techniques to perform classification prediction or anomaly detection). The trust of consumers can be affected because they often have no idea of what led the machine to make this or that decision, leading consumers not to consume the product/service.

1.2. Research Motivation

As with any other business, it is important to understand our consumers, what drives their intention to use/buy/consume, and what causes them to avoid the product or service being offered. In the long-growing field of AI, it is necessary to understand what the consumers' vision of this technology is and how it affects their trust. Indeed, consumers recognize that the data that are captured help to serve them in terms of personalization, but the lack of transparency creates a sense of exploitation (Puntoni, Walker Reczek, Giesler & Botti, 2021) fuelled by actual and perceived loss of control. This is a huge problem to overcome because it leads to a lack of motivation/devotion and helplessness towards AI. However, we have seen that users have positive and approving attitudes towards robots when they have had direct contact with Smart Machines (Savela et al – 2018).

It is important to consider transparency as an essential element within the service that you want to develop and that embeds AI. Indeed, transparency develops in the user a kind of understanding (which can be sustained or superficial), thus leading to an illusion of control over the data take from the consumer (Walker – 2016). In order to accept a product or service that directly integrates AI, it is necessary to take this aspect into account as this will lead to trust and faith in what is offered. Furthermore, trust in AI leads to a certain enjoyment and intention to use (van Pinxteren et al. – 2019). In the domain of service robots, trust appears fundamental for the adoption as service robots are completely new in our daily consumption.

We clearly have a problem of trust in these technologies because they are often perceived as black boxes, not letting you see what is happening inside, making one or another decision. Transparency does not only mean transparency of the algorithm (which we have defined as the black box), but it also means transparency with respect to data and Automated Decision Making (ADM) (Reisman, Schultz, Crawford & Whittaker – 2018). Besides transparency, there is a need to audit algorithms, i.e. checking that they conform to certain properties (Kroll – 2015). Decisions made by algorithms may not be understood or explained and it is not clear who is responsible; that is the problem with the lack of transparency. It is imperative to make progress on the interpretation and transparency of algorithms (Topp, Mair, Smillie & Cairney – 2018) both in terms of business situations (like Machine Learning and Deep Learning research) and for the consumers. It seems important to focus more on the transparency issues concerning AI. Another problem that leads to transparency is the fact that customers and users do not understand how it was thought, built, and used, leading to a lack of transparency with repercussions on trust in something that seems to be unknown.

Therefore, the motivation for the research is to define consumer reluctance towards this technology and how the issue of transparency can affect consumers' trust. It is important to master this aspect knowing that we are still at the beginning of this AI emergence, and that in a few years we will be even more surrounded by AI.

Thanks to this, we hope to be able to provide the elements on which to rely to best reassure the consumer and thus lead him to use products/services that embed AI or Smart Machines. From a managerial point of view, the objective will be to develop an understanding of the transparency issue and how it can impact consumer trust. When consumer trust is gained through a better transparency (and thus a better understanding of what they use or consume), it is then possible to prompt more people to use and consume this type of products and services as they become less worried about AI.

1.3. Academic Motivation

Trust and transparency are already a topic studied in the literature. It is already a noticeably important subject that has been seen in more precise aspects, such as the comparison between a machine and an expert in the context of fine, precise, and heavy responsibility decisions.

In that sector, it is totally important to understand why AI will make a specific prediction because it will have a great impact, whether it is in the world of medicine, engineering, ... Interpretability methods are quickly evolving, offering a better comprehension and explanation inside the black boxes of AI (Ribeiro, Singh & Guestrin – 2016) but there are still many grey areas to explore, especially for unsupervised machine learning models. Nevertheless, those methods bring a precious help in the topic of transparency as it brings a better AI-reading. As explained in the European Commission (2018): "*We need to advance the interpretation, accountability and transparency of algorithms in general and Decision Learning systems in particular*". This is a huge challenge to accomplish as AI technologies continue to evolve very quickly in parallel. Transparency also plays an important role as it is needed to allow audits on algorithms to check that those are conformed to certain properties (Villani, Bonnet & Rondepierre – 2018). Moreover, the lack of transparency (along with the lack of autonomy, privacy, responsibility, and accountability) can have a strong impact on our democratic system (European Commission – 2018).

Beside the legal part, transparency can play a role in the trust accorded to AI Products/services. According to Doug Black (2019), there is an inherent fear of the unknown surrounding this technology and requires understanding lineage of the AI models. Therefore, the Trust gap in AI exists as there is basically only a few (if any) transparencies. This can be explained also because most organizations lack tools and expertise to gain a full understanding and introduce transparency into their algorithms (KPMG – 2019). The main challenge here is how can customers accept those new AI based products/services, even for those who don't fully understand the technology behind. It is also important to understand that transparency and trust in AI just began to appear in the human-computer interaction landscape, allowing more research to be conducted in order to aim for more human-friendly AI products/services (Scharowski – 2020).

The topic on which we will focus in this thesis is the impact that transparency of AI Products/services has on the trust of a consumer with or without AI knowledge. Our main motivation in this work is to understand users' trust towards AI and how the transparency of AI products/services can impact their trust. From this motivation, we can draw axes on which we will focus to give the best perception possible about the problem of trust: the **understanding of the technology used** (a problem of knowledge) and the **problem of black box often posed in the AI world** (the real problem of transparency). We can then formulate our research questions like this:

1) To which extent transparency can influence the consumer trust in AI?
2) To what extent the consumer understanding in the AI drives the consumer trust in AI?
3) How does better understanding of AI could influence the trust in these methods?
4) How can a more transparent AI or Smart Machines influence intent to use/consume?

1.4. Approach

This thesis is composed of two main sections: the theoretical section and the empirical section. The theoretical section consists of a literary review approaching different concepts; The first concept is Customers and AI, where we go deeper into the customers' perception and trust towards AI. The second section includes AI in the business field, where we develop the interpretability for business and the interpretability for AI products/services. The third section includes the Transparency in the AI landscape. Finally, the last chapter of this section includes the definition of our research problem, along with the creation of our conceptual model.

The empirical section addresses our research methodology in the first step. After that, we then check the reliability of our measure's scales, and we end up with analysing our conceptual model. Finally, we finish this thesis with managerial and theoretical recommendations based on our analysis results.

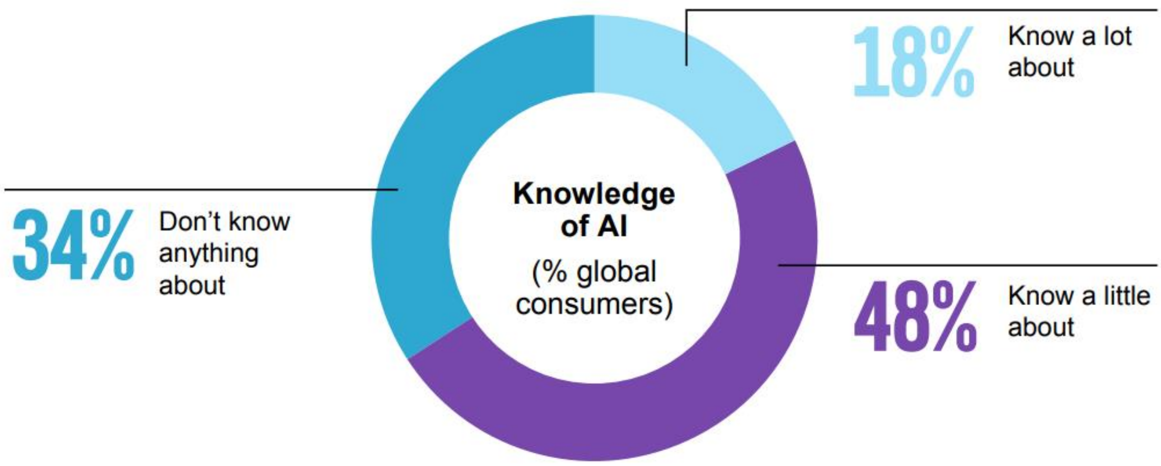
Chapter 2: Literature Review

2.1. Customers and Artificial Intelligence

The service sector has been developing for several years now. Indeed, consumers are increasingly adapting their daily activities through technology (Kunz, Heinonen & Lemmink, 2019), especially with the adoption of AI and automated technologies with Service robots, Chatbots, Virtual Assistants… (Gummerus, Lipkin, Dube & Heinonen – 2019). It is further accepted that automated technology will be increasingly adopted by consumers (Kumar, Dixit, Javalgi, & Dass, 2016). Nevertheless, we can see some problems concerning the trust that is addressed regarding the AI.

Lu, Wirtz, Kunz, Paluch, Gruber, Martins & Patterson (2020) demonstrated that sceptical consumers about AI generally have a limited experience with it and that scepticism is often accentuated by movies and media. Large numbers of the customers collaborated with the thoughts of AI by discovering them in media channels or having people's experiences. Through this, the customers acquire trust in the matter, particularly if it has a productive result. Moreover, many of these individuals have got curious about the use, avenues, and thoughts of AI (Shinn, 2017). With the expansion of AI, customers are concerned about the capabilities and potential that AI has and about the fact that AI could take over every aspect of our lives. The tension coming about because of accepting parts of AI identifies with its confusing nature. To demonstrate this, Weber Shandwick (2018) presented a survey where on 66% of the global customers, eighteen percent professed to know a lot about it while 48% knew a bit. The remaining 34% confessed to knowing nothing about the topic (this is resumed in the figure 9). Indeed, even with these results, the facts demonstrate that a gigantic number of customers believe that they are proficient as far as AI is concerned, a large portion of them could not relate to its simple capacities, for example, problem solving and learning.

Figure 7 Awareness of AI by consumers



It is essential that most of the very many AI-knowledgeable customers see AI in a positive light (Kristin, 2017). They feel it will save time, offer important and improved information access, and allow commitment in perilous tasks (Kaplan, 2017). Customers additionally see that AI will achieve lower prices, companionship, and improved decision regarding purchases. They guarantee that this wonder can offer responses to the complicated issues the world is facing in the 21st century such as incorporate global health, environmental change, pervasiveness of terminal sicknesses like cancer, and economic development. Others additionally accept that AI can help bring mind stability on the issue of privacy, network safety, fraud, individual financial security, and gender equality. Yet other customers also have concerns about machine intelligence (United States, 2016). They bring up that improved progress in AI is probably going to harm employees by taking their responsibilities. Most of the businesses will discover the machines to be more productive making the work force a digital substitution, particularly in office assistant, travel agent, and mentor professions.

2.1.1. The perception of AI by users

AI already has a consistent presence in our daily lives, with over 6.7 million service robots in operation in 2017 (International Federation of Robotics, 2017), service consumers have already been confronted with AI, but if they were not aware of it.

A study was conducted by PEGA to determine what consumers really think about AI. In this study, we can see that 35% feel comfortable with a business AI to interact with them, and 28% who feel uncomfortable. More than a third say that they just do not know yet. Indeed, many consumers are excited about the benefits that AI can provide and see it as having a promising future in the service world. On the other hand, there is a segment of the population that is fearful, preferring human contact. A point of honour in this study is that a large majority of consumers do not understand what AI is and how it affects everyone's everyday life. However, more than 70 percent of the respondents stated that they understand AI. It seems quite impossible as one of the most complex changing technologies in our today's world, and it is proved as half of the respondents do not know that it is able to learn new things, and some do not realize that it can solve problems, recognize images or speeches. In the figure 9, we see the different responses given at the question, "How do you describe what AI can do?" with the capabilities of AI today, the capabilities progressively increasing and the capabilities unlikely in the near future.

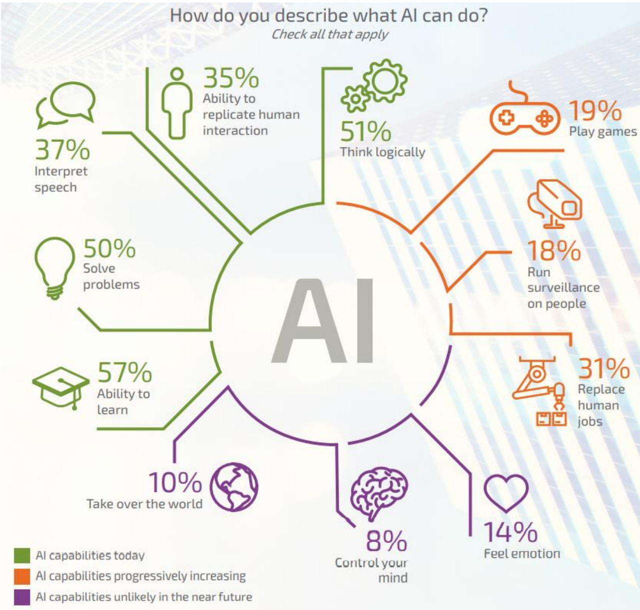


Figure 9 How respondents describe what AI can do

Figure 8 Technologies used or encountered in the last year by Consumers

Going further, the next question is whether respondents have ever used AI, because only 34% believe they interacted with a technology involving AI in the past. Next, the research team asked about the technologies they use in their daily lives (see the figure 10 for the technologies used implying AI), leading to a completely different answer, finding 84% who recently used at least one AI-based service.

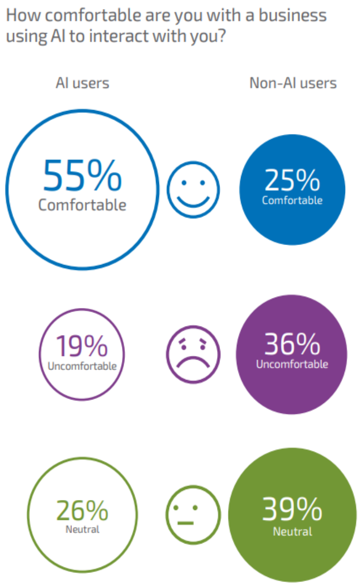


Figure 10 Comfort with the interaction with a business using AI

The matter of misidentifying can be quite normal but is surprising in some case, such as assistants like Alexa, Google Home or Siri, where fewer than 50% knew that there was AI inside those services, even if it is marketed as "*bringing intelligent assistants inside the houses*". The truth behind it is that AI is a victim of many preconceived ideas and a certain mystification. In the study of PEGA (2019), they found out that consumers who used AI have a better understanding about the functioning of AI than non-users and can more easily identify a technology with AI embedded (in the figure 11, we can find the differences between AI users and non-AI users with the comfort of use feeling).

The biggest outcome here is that the most of your customers are knowledgeable and the better it is as they often become your best customers. The understanding and the usage of AI allow an experience of the benefits, making those more open to new technologies with AI embedded, knowing that AI can deeply improve customer experience.

The question is what is really preventing consumers from using technologies with embedded AI? A potential solution would be that many customers still prefer human interactions instead of AI interactions. But the other problem that leads to distrust towards AI is the ignorance of what it is and what is offered, being often driven by movies and media. Most of the time, the fear of AI fades away once the consumer better understands what is being offered behind it and how it works overall.

2.1.2. Consumers' Trust

According to Keng Siau et al. (2018), the level of trust a person has in someone or something can possibly determine the behaviour of this person and can also define the way people interact with technology. Therefore, trust becomes a primary reason for acceptance. Trust in technology is determined by some characteristics, such as ***human characteristics***,

environment characteristics and ***technology characteristics***. We can find in the figure seven the different factors and dimensions of trust in technology.

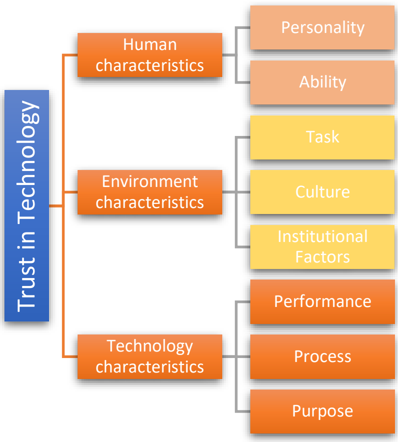


Figure 11 Factors and dimensions of trust in technology.

For the human characteristics, we can consider the human's personality but the trustor's disposition to trust and the ability of the trustee to deal with risk. For the environment characteristics, we consider here the nature of the tasks (a task can be important or trivial), the culture (that can be based on ethnicity, race, religion, or socioeconomic status, and can also be associated with a country or a particular region) and even institutional factors. Finally, we consider in the technology characteristics the performance, the process (and their properties) and the purpose behind the technology.

Trust is especially pertinent to the human-AI relationship because of the apparent risk inserted in human-AI relations, because of the complexity and non-determinism of AI behaviours. AI is also seen as technology that gradually will take over various kinds of (as of now) human jobs. It is yet not satisfactory whether low-skilled and low-cost representatives (for example, frontline service agents) are at a higher risk of being replaced by AI (Huang and Rust, 2018; Pfeffer, 2018; Wirtz et al., 2018) than knowledge labourers and high-level managers. Those kinds of jobs depend on logical and rational knowledge processing, and whose significant expense makes their substitution financially interesting. (Ferràs-Hernández, 2018; Loebbecke and Picot, 2015). In the present, some "human" tasks are now being performed by AI (Brynjolfsson and Mitchell, 2017). Examining tasks across right around 1,000 occupations, Brynjolfsson et al., (2018) tracked down that most occupations in many businesses have probably a few tasks that could be replaced by AI. In any case, there is no occupation where every one of the current assignments could be replaced (Brynjolfsson et al., 2018). There is additionally no conflict that the labour force will go through a dramatic change, for certain positions vanishing and new positions being made (Faraj, Pachidi, and Sayegh, 2018).

Trust is a unique concept that is inclined to changes dependent on the behaviour of the trusted agent (Schoorman et al., 2007, Crisp and Jarvenpaa, 2013;). Hoff and Bashir (2015) said that the route of trust in technology varies from the way it develops itself in people, because of the common inspiration predisposition toward new technologies (Parasuraman and Manzey, 2010). As opposed to the low trust that exists initially between unfamiliar people, new technologies may deliver absurdly optimistic convictions regarding their capacities and functionality (Dzindolet et al., 2003). Consequently, while trust in people and large increases with time through connections, the trust in technology diminishes with time, in view of experiences with errors and malfunctions (Madhavan and Wiegmann, 2007). Be that as it may, the inverse additionally could be true with regards to AI. Calling attention to the boundless suspicion related with the immaturity of existing AI (Hengstler, Enkel, and Duelli, 2016), a few researchers offer that initially low degree of trust from an underlying experience may build following an immediate cooperation (Ullman and Malle, 2017).

Consumers' trust is then critical to the use of a service, making consumer trust a key contributor to the integration of AI in the service industry. Therefore, the consumers' lack of trust is an essential factor to consider (Everett et al., 2017; Morgan, 2017), where marketing research put forward trust as a powerful determinant of intention to use service through enjoyment (Wu and Chang, 2005). To trust AI, the transparency is important, and it would allow to explain and justify the behaviours and decisions that are executed (Siau – 2018). With this lack of interpretability, trust is affected. According to the European Commission in 2018, one of the current challenges in the domain in AI is the interpretability and the transparency of algorithms in general, allowing the society to increase the ability of critical thinking both by respecting AI machines and by challenging them. According to IBM, users (and companies) want AI systems that are transparent, explainable, ethical, trained correctly with appropriate data and with less bias as possible (IBM – 2018). As we have seen above, interpretability became gradually possible, allowing a better interpretability of what the AI does whereas it was previously seen as an opaque black box.

2.2. AI in the business field

In the business field, we can rely on the Artificial Intelligence (AI), which is the use of AI in the goal to improve business operations (Tarafdar, Beath & Ross, 2019). According to Tarafdar et al., AI can automate tasks that are repetitive, allowing a much faster analysis of the information as well as an increased reliability and accuracy of the results. To do so, a domain proficiency is needed to understand everything around AI (the tasks, the workflows, the logic… in order to imagine how AI applications could improve them). Nevertheless, it is important to understand the functioning behind the operation of AI, which happens to be especially important in assessing trust (Ribeiro, Singh & Guestrin, 2018). It is fundamental in the case someone plans to take decisions or action based on a prediction made by a model (in the case of the machine learning for instance). We cannot just trust the model and ignore why it made a certain decision, because the problem is that a single metric such as classification accuracy would be an incomplete description of many of the real-world tasks (Doshi-Velez et al., 2017).

To do so, interpretability presents itself as a potential solution for the business side, in the field of data science working for another party such as the business, commercial and marketing parts. Indeed, it allows each business or commercial parties to understand the prediction made (whether experts or people without knowledge concerning Machine Learning).

2.2.1. Interpretability in Machine Learning

Interpretability is the degree to which a human can understand the cause of a decision (Miller, 2019) or even the degree to which a human can consistently predict the model's result (Kim et al., 2016). In our situation, we will use the definition stated by Miller, and we will also talk about the cause of a prediction or some advice. Also, when we talk about explanations, we talk about explanations of individual predictions.

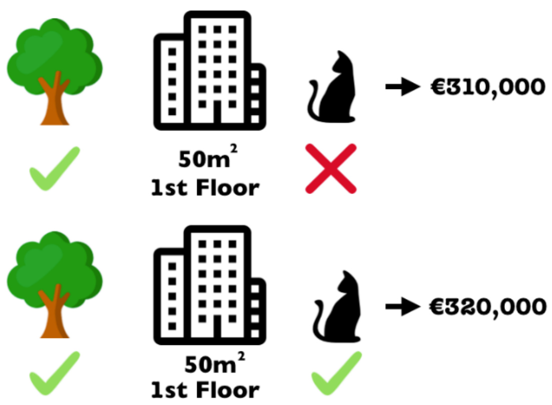
As the Machine Learning is a huge part of AI (section that allowed for instance automatic pilot cars, image recognition, …), the interpretability of those models can be a strong base for AI in general. If you can have a high enough interpretability, it would be easier for someone to comprehend the behaviour and the suggestions of a model in order to help in the decision process. In the case of the machine learning, it is important because a model will be more interpretable if the decisions are more understandable for a human (Molnar, 2020). Interpretability remains important; Why can't we just trust the model and ignore why it made a specific decision? The reason we are not able to do it is because the problem is a single metric such as classification accuracy is an incomplete description of most real-world tasks (Doshi-Velez & Kim, 2017).

Multiple interpretability methods have been developed, and one of the best-known methods is based on coalition game theory, the Shapley Values, and its derivative: SHAP (Molnar, 2020). This method relies on the fact that a prediction can be explained by assuming that each feature value of the instance is a player in a game, and the prediction is the pay-out. Thanks to Shapley Values, we can distribute fairly between the different features.

The Shapley Value is a method that assigns payoffs to the different players based on their contribution to the total payoff. Players co-operate in a coalition and receive some benefit from this co-operation (Shapley, 1953).

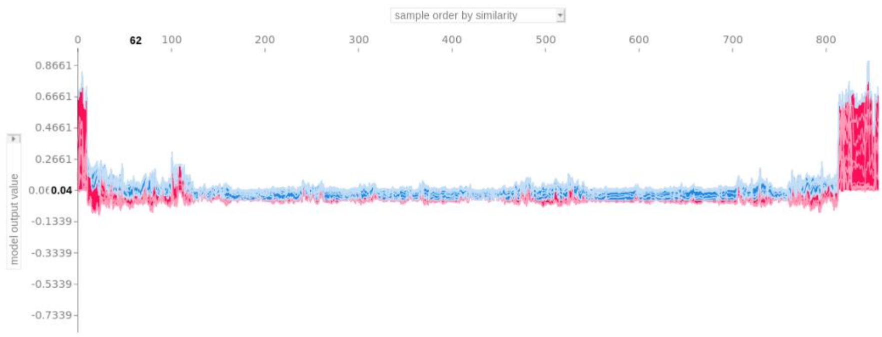
An example in interpretability can be given in the case of the price estimation of a flat. Based on the figure below, the players the following features: the flat has a park nearby or not, and can are allowed or not, the surface of the flat and at which floor it is situated. A value is assigned to each feature for a given flat, and this value represents the average marginal contribution of a feature value across all possible coalitions (meaning that the feature of a flat is compared to the contribution of the same feature for the other flats).

Figure 12 Example of Shapley Values for a flat



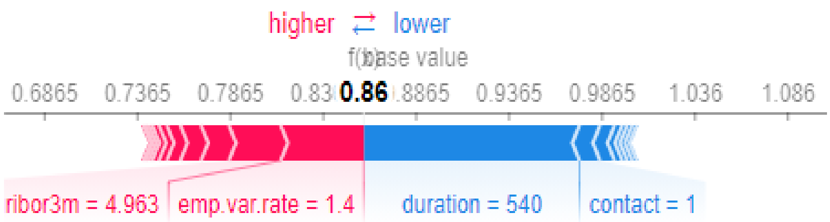
From this method, a derivative of this method was created to explain individual predictions: SHAP (SHapley Additive exPlanations) and is totally based on the game theoretically optimal Shapley Values (Lundberg and Lee, 2017). SHAP allows global and local interpretations, and offers multiple approaches built for the different supervised learning. On the figure X, a global interpretation is made, stacking the different SHAP explanations clustered by explanation similarity.On the X-axis, every position is an instance of the data. The values in red are increasing the prediction and the values in blue decrease it.

Figure 13 Example of Global Interpretation (SHAP)



On the figure X, we have the SHAP values that explain the prediction of an instance. The logic with the colour is the same as for the global explanation: the red colour pushes positively the prediction, and the blue pushes it negatively.

Figure 14 Example of Local Interpretation (SHAP)



2.2.2. Explanations of decisions

First, it is important to define what is an explanation. An explanation is the answer to a why-question (Miller, 2019) such as "*Why did not the treatment work on the patient? Why was my loan rejected?*". To make a good explanation, several implications have been created. A good explanation is necessary if we want to be as interpretable and transparent as possible. On this point, Miller condensed the basic of a what is a good explanation, adding implications for interpretable Machine Learning.

Explanations are contrastive (Lipton, 1990), meaning that people do not want the total explanation of a prediction, but the differences that allow to compare the prediction with another instance's prediction (even if it is artificial).

Also, ***explanations are selected***, because people need explanations that are noticeably short, they don't need explanations that cover the complete causes of the prediction.

Explanations are social, as we need to consider the social environment of the Machine Learning application and the target. We often rely on experts to help in this social part.

Explanations focus on the abnormal (Kahnemann and Tversky – 1981), meaning that an abnormal input feature (such as a rare category) that influences the prediction might be the best explanation for the prediction made.

Explanations are also truthful, meaning that the explanation can predict the event (this is often called the fidelity). It means that the explanation might be true for another instance.

Finally, ***good explanations are general and probable***, meaning that a generality can be measured based on the feature's support (what we can call the number of instances where we have the explanations applies divided by the total instances).

With the help of social sciences, we can define what is a good explanation from the user's perspective, and it is important to have those properties of explanations in mind. In the section of interpretable machine learning, it helped to create models that allow a good understanding of what happened in the model (T. Ribeiro et al., 2019). Nevertheless, explanations will also be important in the field of Marketing, to influence customers' trust in the right direction as they need to understand at least a little what they consume. We will develop this part further.

2.2.3. Limitations and future of Interpretability Methods

Indeed, interpretable Machine Learning is limited in the field of business because interpretability remains to people with a minimum of business and Machine Learning knowledge and thus depends on the expertise of the concerned people. As we will see in this part, we find the limitation of time and knowledge concerning the field of Machine Learning.

As seen before, interpretability is mainly Machine Learning oriented requiring a model. Indeed, machine learning is still widely used in a business aspect, allowing to justify the decisions of a model before an application or actions that are taken (Molnar, 2020). In the banking world for example, customer classifications can be made (risky customers for example) and thus facilitate decision-making according to this data (for example, to increase the spending limit for a Visa card). Therefore, it is necessary to have a deep understanding of the model before applying it in real cases, requiring people having the minimum knowledge of the world of AI (and particularly in machine learning in our case).

There is also another limitation that restricts the interpretability in the business domain; it is the **execution time**. Indeed, strong interpretability methods have a huge time constraint (Molnar, 2020), with an exponential evolution depending on the number of instances and the number of features. Some methods require to train 2^F models, with F being the number of all features available (Mazzanti, 2021). This is a real concern as we need in some cases a quicker interpretation of the results in order to make quick decisions (for instance in a highly competitive market).

According to Molnar, the future of interpretability will be the automation (as it is being done for the automation of model training), allowing robots and programs to explain themselves, thus giving a boost to the research of machine intelligence and to the adoption of the machine learning in enterprises. It is important to really take into consideration the Machine Learning knowing that it will allow a lot of automation such as sorting, decision-making, data-driven decisions such as credit applications, drug discovery, self-driving cars, diagnosis of diseases, translation, etc. This automation will strongly be followed by the interpretability, allowing robots and programs to explain themselves in a more or less near future.

2.3. Transparency

Recent researches have already highlighted the growing importance of AI transparency in the service world (Arnold et al. 2019). Even if the transparency is a topic that has been well studied, there is, however, only few discussions of this in the service sector, which is aimed towards the consumer and the perception of the consumer. According to Ostrom & al. in 2019, a lack of transparency can lead to significant potential for negative outcomes, and this lack of transparency is linked with the problem of interpretability. However, this can lead to an important problem in some situations such as healthcare, financial services, emergency services and can have consequences on the consumers' well-being (Knight, 2017). The transparency in those sectors remains crucial as it leads to important decisions on the consumer's life in some moment. The combination of ethical issues of transparency with AI and the lack of trust generated the need of AI models that can be explained, leading to the creation of explainable AI, also known as XAI (Pawar et al. – 2020). Transparency is a multilayered concept used by different disciplines (Margetts, 2011; Hood, 2006). In recent times, it has gone through a resurgence concerning contemporary discourse's AI. For instance, the ethical guidelines distributed by the EU Commission's High-Level Expert Group (AI HLEG) in April 2019 states Transparency as one of seven key requirements for the acknowledgment of 'trustworthy AI', which additionally has made it clear imprint in the Commission's white paper on AI, published in February 2020. Indeed, Transparency is the absolute most common, and one of the five key standards accentuated in the vast number of ethical guidelines tending to AI on a worldwide level (Jobin et al., 2019).

When we talk about transparency in the context of AI, a link is made in the literature referring itself both to interpretability as well as trust in the systems (Ribeiro et al., 2016). When assessing consumers' trust in AI, an assumption that comes from recent literature is that the issue of transparency must consider how basically humans understand explanations, and also the way they assess their relationship to a service, a product or even a company (Miller, 2019). The building of explainable AI is driven by evidence that a lot of AI applications are not used in practice, and it is due to users with a lack of trust in those applications (Linegang et al., 2006). From one perspective, AI without a doubt is a challenged concept that needs clear agreement, both in software engineering (Monett, Lewis and Thórisson, 2020), law (Martinez, 2019) and the public perception (Fast and Horvitz, 2017). This is connected to the way that intelligence alone has been characterized in any event 70 distinct manners (Legg and Hutter, 2007). Moreover, the definition has changed as the conceivable outcomes inside the field has created since its beginning during the 1950s, presenting what in some cases is known as the "AI impact" or an "odd paradox" (Stone et al., 2016; McCorduck and Cfe, 2004) as in once an issue seen as requiring AI has been settled, the application stops to be seen as intelligent. This relates to the view that AI is tied in with problem solving that computers at present cannot do, and when it is workable for a computer to settle it, it no longer considers an AI-problem. In this way, the difficult to-characterize field of AI has fittingly been tended to as not a solitary technology, yet rather "a set of strategies and sub-disciplines going from areas like speech recognition and computer vision to consideration and memory, to give some examples" (Gasser et al., 2017).

2.4. Definition of the research question and conceptual model

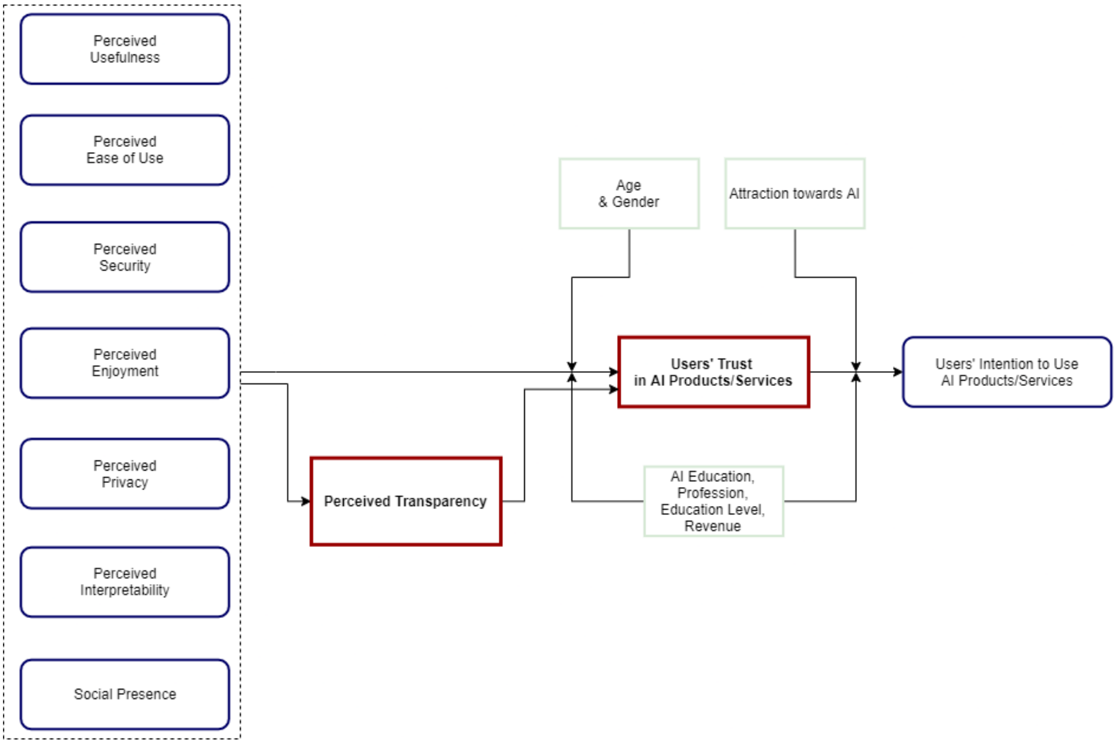
In this section, we will present the research question, the objective of the research and the conceptual model. Through the conceptual model, we will discuss the different underlying hypotheses considering the literature.

2.4.1. Research question and conceptual model: Hypothesis and variables

The main objective of our work is to evaluate the impact that transparency can have on consumer trust, and thus the impact it can have on the usage of products or services with embedded AI. As said before, products and services integrating AI are more and more widespread, leading a maximum of consumers to consume AI sometimes without even understanding what is behind. The consumers' trust being rather well impacted concerning AI, it has already been noticed that this was mainly due to a lack of knowledge about what it concretely is. In our work, we will try to determine the impact that transparency can have on the trust that is granted by consumers. In the world of technology, AI is becoming an increasingly important part of our everyday lives, and we can expect an exponential growth in the coming years. Indeed, according to Lu et al (2020), AI could have a deep impact on the service industry. Therefore, it is important to gain the consumer's trust to have a maximum of satisfied customers for the product/service. To do so, we will start from the values perceived by consumers towards AI, to see if there is indeed an impact due to transparency on consumer trust. To do so, we will focus on 2 categories of people: AI consumers who did not understand how the product/service works and AI consumers who understood how the product/service works. The goal here is to measure the difference in trust between these two groups and to understand if transparency is involved in any way.

To best define our conceptual model, we will start from the values that a customer may perceive when using a product or service with embedded AI, with the overall evaluation that comes from the consumer's own experience. In addition, we will add the variable of transparency, with the aim of finding out how important transparency matters in the trust that the consumer has in AI. With this conceptual model, we assume that transparency will indeed have an impact on consumer trust in AI. This trust should normally impact the use of products/services with embedded AI. We also use moderator variables such as attraction to AI as well as age and gender.

Figure 15 Conceptual Model



2.4.1.1. Trust and components

Perceived Usefulness & Perceived Ease of Use

Davis (1989) defined the Perceived Usefulness as "*one of the most independent constructs in the Technology Acceptance Model [TAM] and is the degree to which a person believes that using a particular system would enhance his/her job performance*". Davis also described the Perceived Ease of Use as "*the degree to which a person believes that using a particular system would be free of effort*". To examine users' adoption towards new technologies, we can find multiple TAM. We will focus here on the TAM of Davis (1989) as it is one of the most appreciated by the researchers as it conveys the importance of functional attributes of technologies for their adoptions by users.

Perceived Usefulness and Perceived Ease of Use are often considered fundamental predictors (Wirtz et al., 2019), but TAM is often criticized as being outdated with a lack of sufficient depth that could help to present the adoption of newer technologies (Lim, 2018). As a result of this finding, other methods appeared such as UTAUT and UTAUT2, on which we will focus more in the following points. It appears that a customer's intention to use a new technology will have a certain dependence on the cognitive evaluation about the perceived usefulness such as the perceived ease of use (Davis, 1989), as there are representing the core of TAM. Those variables have already been studied, and the effects have been documented through the literature (especially in the e-commerce) (Cyr et al., 2007; Hassanein & Head, 2007; Moriuchi, 2019; Ye et al., 2019), and it has been demonstrated that functionality has an impact in terms of usability (Chen & Dibb, 2010), ease of use and Perceived Usefulness (Lu et al., 2016). We can then elaborate some hypothesis based on the foundations of TAM (Davis, 1989) such as other literature.

H1: Perceived Usefulness of AI products/services will have a positive influence on consumers' trust towards AI.

H2: Perceived Ease of Use of AI products/services will have a positive influence on consumers' trust towards AI.

Perceived Security

Perceived Security refers to the customer's subjective evaluation of the system's security (Linck, Pousttchi & Wiedemann – 2006). Furthermore, it will depend on their experiences and expectations, adopting attitudes towards the security. If the level of perceived security is too low, users will be more reluctant to use the product until solutions are added in order to reassure them (Tsiakis and Sthephanides 2005). Therefore, we can see a relation between security and trustworthiness, which are the main concerns for users (Linck et al. – 2006). We can then elaborate a hypothesis based on the work of Kim et al. (2010):

H3: Perceived Security of AI products/services will have a positive influence on consumers' trust towards AI.

Perceived Enjoyment

Previous research has highlighted that users are motivated by hedonic benefits when interacting with technology (Wu et al., 2010). The UTAUT2 model from Venkatesh et al. (2012) observe that the functional properties that a technology offers is not enough to fully establish users' intention to use. After incorporating hedonic motivation into their well-known previous model (UTAUT), they found out that users' enjoyment while having an interaction with the technology can influence its actual and future use (Pizzi & Scarpi, 2020). Also, the role of enjoyment has been set as an actor in the influence of consumers' use and adoption of mobile apps, demonstrating that fun and perceived enjoyment (intrinsic motivators) can be stronger than extrinsic motivators such as Perceived Usefulness for example (Fong et al., 2018). More than impacts on consumers' behaviours, perceived enjoyment and pleasure of interacting with a new technology can have an influence on loyalty and trust (Hwang & Kim, 2007; Ogonowski et al., 2014). In the situation of AI products/services, it makes sense as consumers' interactions with AI products/services embedded can give to consumers valuable benefits in terms of enjoyment while using the product/service. Based on the foundation found in UTAUT2 (Venkatesh et al., 2012) and the TAM (Davis et al., 1992), we can formulate the following hypothesis:

H4: Enjoyment of AI products/services will have a positive influence on consumers' trust towards AI.

Perceived Privacy

AI often requires access to the user's private data to serve the user in the best possible way to provide oriented answers or advice, or to serve the user better. However, this can be problematic in the eyes of the user, who will perceive privacy risks. Respecting privacy is important as a lack of privacy can cause users to lose confidence in the AI product/service they are using. The privacy risks are defined as the fear of unauthorized access to their intimacy by others, potentially leading to unauthorized disclosure of customers' personal information (Han & Yang, 2018). Furthermore, a multitude of research has demonstrated the negative impact that the perception of privacy can have on trust but also on consumer behaviour (Zhou, 2011). Indeed, consumers' privacy problems will have a negative impact on the trust given to the AI product/service and on the subsequent behavioural intention, both in terms of the purchase, revisit and also in positive recommendations (Liu et al., 2005). Also, Chang et al. (2017) demonstrated that perception of privacy has a negative impact on users' trust and the intention to use social media. This problem of privacy linked to social networks can easily be put in parallel with AI products and services. Privacy risk has a negative impact on trust, knowing that trust has a total positive influence on willingness to adopt (Dinev & Hart, 2006), and this is the foundation for the effects of privacy problems. It therefore makes sense to integrate the EPCM (Dinev & Hart, 2006) into our variable of privacy, allowing us to establish a hypothesis:

H5: Privacy concerns of AI products/services will have a negative influence on consumers' trust towards AI.

Perceived Interpretability

Interpretability is the degree to which a human can understand the cause of a decision, a prediction or even advice (Miller – 2019). This is a huge concept linked to transparency as it allows people to have a better understanding of the AI results (Kim et al., 2016) and is mainly used in the business part (for instance with machine learning). We are only starting to talk about interpretability in the literature, and there are only a few articles talking about perceived interpretability by consumers. Therefore, our goal here is to put perceived interpretability forward as being a driver for transparency. Based on the business interpretability literature, we draw this hypothesis for the users' perception of interpretability.

H6: Perceived Interpretability will have a positive influence on consumers' trust towards AI.

Perceived Social Presence

Social presence is "the degree of importance of other people during an interaction"(Short et al., 1976), and for automated systems such as AI, it is the "extent to which technology makes customers feel the presence of another social entity" (Van Doorn et al., 2017). It has been demonstrated that people tend to give social roles when they are using technology, and thus treat them as a social entity and this is particularly true for technologies that will mimic human attributes. AI can take many forms that can be assigned to human attributes, such as speech and virtual face, which can give to the user the impression of social presence (Chattaraman et al., 2019). Derived from the Social Response Theory (SRT), social presence is important to consider as it can influence online behaviours (Chung et al. 2015) and on trust building (Gefen & Straub, 2003, 2004). Due to an often-great aptitude of AI to take human attributes, AI may offer a social presence in the interaction between to products/services and the consumer. Based on the foundations of SRT, we can build the following hypothesis:

H7: Perceived Social Presence of AI products/services will have a positive influence on consumers' trust towards AI.

2.4.1.2. Perceived Transparency

Transparency is a topic that takes up more and more space as recent research has highlighted the growing importance of AI transparency in the service world (Arnold et al., 2019). In our work, we will try to define what exactly is the impact of transparency on consumers' trust towards AI products/services. According to Ostrom & al. in 2019, a lack of transparency can lead to significant potential for negative outcomes. This lack of transparency is easily linked with the interpretability in the business field, but the exception here is that it must be addressed to consumers. Interpretability methods are irrelevant in that situation as it requires a minimum of AI knowledge and time to analyse why the AI made such a decision. Furthermore, interpretability methods are especially marked in the machine learning field.

The lack of transparency can lead to important issues in some situations such as healthcare, financial services, emergency services… and can have consequences on the consumers' well-being (Knight, 2017). It is thus completely relevant to work on transparency in the goal to gain consumers' trust, which is an influencer of intention to use. As the transparency can lead to a better comprehension, it is then important to have a deep focus on that part a build a better on transparency in order to create products and services more trustworthy. Therefore, we can establish the following hypothesis:

H8: Perceived Transparency will have a positive impact on the Users' Trust towards AI products/services.

2.4.1.3. Consumer Trust and Intention to Use

In our work, we are trying to define the impact that transparency can have on trust. However, to have a better understanding of the consumer's trust, we decided to also study consumers Use Intention with AI. We will first focus on consumer trust and then discuss in deeper details consumers Use Intention because of consumer trust.

As presented by Keng Siau (2018), the level of trust of a person has in someone or something can determine the behaviour of this same person, defining the way people can interact with technology. Also, trust becomes one of the main reasons for acceptance, and this is the reason why the consumer's lack of trust is an essential factor to consider (Everett et al., 2017; Morgan, 2017), where marketing research put forward trust as a powerful determinant of intention to use service through enjoyment (Wu and Chang, 2005). However, trust may also be impacted by irrational elements, like feelings and state of mind (Komiak and Benbasat, 2006). McAllister (1995) alluded to the last as emotion driven or influence based trust, offering that in relational connections, individuals foster social associations that support and comfort. In the situation of AI, emotions can have a big impact as it is something new, and that it arouses a certain interest guided by the unknown, excitement and even fear (sometimes fuelled by fiction). The Use Intention is the expression of the discreet probability that a consumer will use a specific thing in a defined period (Dimitriadis et al., 2010). There is a strong link between intention and behaviour, based on the assumption that people make rational decisions that will be influenced by the information they have. Based on that, we make the following hypothesis:

H9: Consumers' trust towards AI Products/services has a positive influence in their Intention to Use AI Products/services.

2.4.1.4. Moderator Variables

Age, Gender, Profession, Education Level and Revenue.

Socio-demographic characteristics such as age and gender are often used as moderator variables. Shi et al. (2016) studied the impact of customer gender on their perceived values when interacting with a brand in the context of social media. Their study found that, in general, men are motivated to continue their interactions with the brand because of the functionality they perceive, while for women it is more about social and enjoyment. Therefore weformulate the following hypotheses:

H10: Age is a moderator variable of the relation of the various components of the user experience with AI and customers' trust in AI.

H11: Gender is a moderator variable of the various components of the user experience with AI and customers' trust in AI.

Attraction towards AI

As AI is a growing part of the technology field, we can clearly generalize the attraction towards AI as the attraction towards technology. Agarwal and Karahanna (2000) argue that an individual's technology use behaviour will be significantly impacted based on his or her perception/belief about the technology. Therefore, we can make the following hypothesis:

H12: The Attraction towards AI is a moderator variable of the customers' trust in AI and Intention to Use AI Products/services.

Education in AI

A lot of people remain afraid of AI, and it is mainly due to a lack of knowledge. A study realized by PEGA tried to determine what consumers really think about AI. In this study, we can see that 35% feel comfortable with a business AI to interact with them, and 28% who feel uncomfortable, and more than a third just do not know yet. Furthermore, only 34% thought that they had an experience with AI in the past which is actually wrong with at least 84% of the respondents that have already used AI (Email spam filters, predictive search terms…). The biggest outcome here is that most of your customers are educated which it is good as they often become your best customers. The understanding and the usage of AI allow an experience of the benefits, making those more open to new technologies with AI embedded, knowing that AI can deeply improve customer experience. The education will probably have an impact on consumers' trust and thus on the Intention to Use. Therefore, we can make the following hypothesis:

H13: Transparency in AI Products/services is a moderator variable of the various components of the user experience with AI and customers' trust in AI (H11a) and of the customers' trust in AI Products/services and Intention to Use AI Products/services (H11b)

Chapter 3: Research Design

3.1. Methodology

The main objective of this section is to present the methodology that was used in this thesis. In this section will be discussed the questionnaire redaction and the data collection.

3.1.1. Questionnaire redaction

We created a quantitative survey to test our assumptions of the conceptual model. We have been able to collect 153 answers (with 142 that were valid). The survey is divided in four parts. First, respondents are asked to read a short introduction that explains the main goals of the survey as well as other information such as the anonymity of their responses or even the duration of the survey.

The first part of the survey starts with a question to know if they use AI or not. In case they answer negatively, another question is asked to check that they have never used an AI product/service through examples of everyday use. If they answer negatively, that marks the end of the survey for them. After that, a small point on AI is made to put all respondents on the same footing regarding AI. For the positive answers, we ask the questions about his behaviours towards AI (its expenses, its frequency of use, ...) and the questions that aims to evaluate his intention to use AI products/services. After the first part, a small point on AI is made to put all respondents on the same level regarding AI.

The second part aims to define the perception that users have towards AI, and where we try to estimate trust, perceived usefulness, perceived ease of use, perceived security, enjoyment, perceived risks, and the social presence.

The third part aims to define the different properties of AI, we try there to estimate the attraction towards AI, AI education and transparency of AI.

The fourth and final part includes socio-demographic questions.

3.1.2. Data Collection

The survey has been shared on social networks (Facebook, LinkedIn and Instagram) to try to collect as many answers as possible, but we also reached people by email (we targeted people with low use of AI). Overall, 153 answers have been collected with 142 that were valid. The non-valid answers were from respondents who do not use AI products/services (through the filter question in the first part), and that is the reason why we deleted those data.

3.2. Measures

In this section, we will present the measures that we will use for the different variables. After that, a pre-test will be executed to valid our questionnaire. We will give a little presentation of the sample and we will finish by measuring the reliability of our scales.

3.2.1. Measurement of variables and choice of scales

3.2.1.1. Dependant Variables

Intention to Use.

The **Intention to Use** is measured by three items based on the work of McLean and Osei- Frimpong (2019), and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".

Table 1 Adaptation from McLean and Frimpong (2019)

INTU1: It is likely that I will use AI products/services in the future.
INTU2: I intend to use AI Products/services frequently.
INTU3: I expect to continue using AI Products/services in the future.

Transparency

Transparency is measured by six items based on the work of Bertot et al. (2010), and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".

Table 2 Adaptation from Bertot et al. (2010)

TRA1: The AI Product/Service allows me to track my activities.
TRA2: The AI Product/Service provides information about the decisions and actions.
TRA3: The AI Product/Service provides information on the rules and regulations
TRA4: The AI Product/Service disseminates information on the own performance.
TRA5: Overall, AI Product/Service has an enhanced transparency on what it does.

Trust

The **Trust** is measured by six items based on the work of Chattaraman et al. (2019), and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".
Table 3 Adaptation from Chattaraman et al. (2019)

Table 3 Adaptation from Chattaraman et al. (2019)

TRU1: AI Products/services competently and effectively interact with me.
TRU2: AI Products/services perform all their roles very well.
TRU3: Overall, AI Products/services are capable and proficient.
TRU4: AI Products/services are truthful to me.
TRU5: I would characterize AI Products/services as being honest.
TRU6: AI Products/services are sincere and genuine.

3.2.1.2. Independent Variables

Perceived Usefulness

The **Perceived Usefulness** is measured by four items based on the work of Davis (1989) as well as the work of Davis et al. (1989) study, and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".

Table 4 Adaptation from Davis et al. (1989)

PU1: I think that using AI products/services would enhance the effectiveness of my AI consumption.
PU2: I think that the use of AI products/services would be useful to me.
PU3: I think that using AI products/services in my consumption would increase my productivity.
PU4: Overall, I find AI products/services useful in my consumption.

Perceived Ease of Use

The **Perceived Ease of Use** is measured by four items based on work of Davis (1989) as well as the work of Davis et al. (1989), and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".

Table 5 Adaptation from Davis et al. (1989)

PEU1: Interacting with AI products/services would not require a lot of mental effort.
PEU2: I think that working with AI products/services is as easy as working with humans.
PEU3: Learning how to use AI products/services would be easy for me.
PEU4: Overall, I find AI products/services easy to use.

In the Perceived Ease of Use, we add the concept of **Interpretability**. As interpretability has not been studied in a quantitative situation, we decide to offer a short scale that could allow an estimation of interpretability.

I1: The outcome (advices, predictions or decisions) of the AI Product/Service is clear to me.
I2: I can easily interpret the outcome (advices, predictions or decisions) of the AI Product/Service and why it produced such an outcome.
I3: I can easily explain the outcome (advices, predictions or decisions) of the AI Product/Service and why it produced such an outcome.

Perceived Security

The **Perceived Security** is measured by four-items based on the work of Kim et al. (2010), and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".

Table 6 Adaptation from Kim et al. (2010)

PS1: I perceive AI Products/services as a secure technology.
PS2: I perceive the information relating to interaction between user and AI products/services as secure.
PS3: The information I provided in previous interaction with AI products/services is helpful for the further interactions.
PS4: I do not fear hacker invasions into AI products/services

Perceived Enjoyment

The **Perceived Enjoyment** is measured by four items based on the work of Mun and Hwang (2003), and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".

Table 7 Adaptation from Mun and Hwang (2003)

PE1: I find AI products/services interesting.
PE2: I find AI products/services entertaining.
PE3: I enjoy using AI products/services.
PE4: I find AI products/services pleasant.

Perceived Privacy

The **Perceived Privacy** is measured by three items based on the work of Zhou (2011), and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".

Table 8 Adaptation from Zhou (2011)

PPR1: It is risky to provide personal information to an AI product/service.
PPR2: There will be much uncertainty associated with providing personal information to an AI product/service.
PPR3: There will be much potential loss associated with providing personal information to AI product/service.

Social Presence

The **Perceived Enjoyment** is measured by five items based on the work of Gefen and Straub (2004), and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".

Table 9 Adaptation from Gefen and Straub (2004)

SP1: There is a sense of human contact with AI.
SP2: There is a sense of personalness with AI.
SP3: There is a sense of sociability with AI.
SP4: There is a sense of human warmth with AI.
SP5: There is a sense of human sensitivity with AI.

3.2.1.3. Moderator Variables

Attraction towards AI

Attraction towards AI can be measured through seven items based on the work of of the research of Agarwal and Karahanna (2000) and Venkatesh (2000), and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".

Table 10 Adaptation from Agarwal and Karahanna (2000) and Venkatesh (2000)

AAI1: Usually, I never hesitate to try new AI product/service
AAI2: Among my relatives, I am always the first to try new AI product/service
AAI3: I like to experiment with new AI product/service
AAI4: Using AI product/service makes me nervous
AAI5: I am apprehensive about using an AI product/service
AAI6: I don't use an AI product/service because I am not familiar with them
AAI7: I hesitate to use an AI product/service for fear of making mistakes

AI Education

AI Education can be measured through seven items based on the work of the research of Naci Çoklar & Ferhan Odabaşi (2009), and a seven-point Likert scale ranging from "strongly disagree" to "strongly agree".

Table 11 Adaptation from Çoklar & Ferhan Odabaşi (2009)

AIE1: I can explain how AI products/services operate.
AIE2: I can use AI products/services in different ways.
AIE3: I can do basic things regarding AI technology.
AIE4: I can explain general concepts related to AI technology.
AIE5: I can use AI products/services effectively.

Age, Gender, Education Level, Profession and Revenues

Age is measured by asking to the respondent in which of the ten categories established he relies to. G**ender-wise**, the respondent is asked if he/she is a man or a woman. The **Profession** will be determined by asking to the respondent in which of the seven categories he identifies himself to. For the **Revenue**, the respondent will have the choice between six categories. Those questions will be available at the end of the questionnaire.

3.3. PreTest

We first sent our questionnaire to a small number of people (about 5) to see if the questions were well formulated and understandable, if the length of the survey was correct, and to see if there were any other problems that might be present. We have been able to rewrite some questions that were not understandable for our pre-test respondents, helping us to make more understandable sentences (specifically for respondents with a low understanding of AI). Also, we have understood that a lot of people did not really know what AI was. To solve this issue, we decided to make a quick explanation about what we mean by "AI Products and Services", to be sure that the different respondents understand it in the same way as others. Also, this pretest helped us to see the average time to complete the survey: the quickest was around 5 minutes (320 seconds) and the longest was around 10 minutes (630 seconds). This helped us to estimate how long the survey would take respondents.

3.4. Presentation of the sample

Our sample is composed of 142 people. In this sample, **54.2%** of the respondents are women and 45.8% are men. The most common age category is 19-25 years old (**56.3%**). **8.4%** of the respondents are in the age category (26-30 years old) and **26.05%** are older than 31 years old. We also have 35.9% of the respondents that are students and 28.8% that are employees. Concerning the level of education, 57% have a university education level and 27.4% have a higher non-university education level. Finally, regarding the amount spent on AI products/services, 28.1% spend 0€ for AI products/services, 21.1% do not know how much they spend for AI products/services, 10.5% spend between 10 and 19.99€ for AI products/services and 10.5% spend between 20 and 29.99€ for AI products/services.

3.5. Measuring the reliability of scales

In this part, we will check the reliability of our scales. Most of our constructs are composed of several items and we need to ensure that these items measure the dimension we are trying to assess. To do so, we first carry out a factor analysis to ensure that the constructs represent the dimensions we are trying to study. This analysis consists of three steps/conditions to be checked:

- Final commonalities are greater than 0.5
- Correlations between items and factors are greater than 0.6
- Cross-loadings are less than 0.3

To be selected, an item must fulfil these three conditions.

In the continuity of the reliability analysis, we must ensure the internal consistency of items within a scale. In other words, it means that we must check if the items have much in common within the same scale, and we will use Cronbach's alpha to check that. The formula used is the following one (Durant, 2003):

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_{Y_i}^2}{\sigma_X^2}\right)$$

Where k is the number of items, $\sigma_{Y_i}^2$ is the item variance and σ_X^2 is the variance of the total score.

Cronbach's alpha is a coefficient that varies between 0 and 1; The closer the value of this coefficient is to 1, the higher the internal consistency of the scale and hence the higher the reliability. We will consider scale reliable when Cronbach's alpha is between 0.7 and 0.8 (Nunnally, 1978). You can find below a summary table in which the results of the factor analyses for each construct are summarized with the items remaining after analysis, the number of items remaining and the Cronbach's Alpha. Details of these analyses can be found in Appendices.

Table 12 Summary of the selected items for each construct

Construct	**Items**	**Number of Items**	**Cumulative percentage variance**	**Cronbach's Alpha**
Intention to Use	**INTU1**: It is likely that I will use AI Products/services in the future. **INTU2**: I intend to use AI Products/services frequently. **INTU3**: I expect to continue using AI Products/services in the future.	3	78.2%	0.857
Transparency	~~**TRA1**: The AI product/service allows me to track my activities.~~ **TRA2**: The AI product/service provides information about his/her decisions and actions.	4	59.4%	0.7715

	TRA3: The AI product/service provides information on his/her rules and regulations. **TRA4**: The AI product/service disseminates information on his/her own performance. **TRA5**: Overall, AI product/service has an enhanced transparency on what it does.			
Trust	~~**TRU1**: AI products/services competently and effectively interact with me.~~ ~~**TRU2**: AI products/services perform all their roles very well.~~ ~~**TRU3**: Overall, AI products/services are capable and proficient.~~ **TRU4**: AI Products/services are truthful to me. **TRU5**: I would characterize AI Products/services as being honest. ~~**TRU6**: AI Products/services are sincere and genuine.~~	2	83.7%	0.8055
Perceived Usefulness	**PU1**: I think that using AI products/services would enhance the effectiveness of my AI consumption. **PU2**: I think that the use of AI products/services would be useful to me. **PU3**: I think that using AI products/services in my consumption would increase my productivity. **PU4**: Overall, I find AI products/services useful in my consumption.	4	69.7%	0.8538
Perceived Ease of Use	~~**PEU1**: Interacting with AI products/services would not require a lot of mental effort.~~	2	82.1%	07789

	~~**PEU2**: I think that working with AI products/services are as easy as working with humans.~~ **PEU3**: Learning how to use AI products/services would be easy for me. **PEU4**: Overall, I find AI products/services easy to use.			
Perceived Ease of Use - Interpretability	**I1**: The outcome (advices, predictions or decisions) of the AI product/service is clear to me. **I2**: I can easily interpret the outcome (advices, predictions or decisions) of the AI product/service and why it produced such an outcome. **I3**: I can easily explain the outcome (advices, predictions or decisions) of the AI product/service and why it produced such an outcome.	2	85.2%	0.8243
Perceived Security	**PS1**: I perceive AI products/services as a secure technology. **PS2**: I perceive the information relating to interaction between user and AI products/services as secure. ~~**PS3**: The information I provided in previous interaction with AI products/services is helpful for the further interactions.~~ ~~**PS4**: I do not fear hacker invasions into AI products/services~~	2	84%	0.8094
Perceived Enjoyment	~~**PE1**: I find AI products/services interesting.~~ ~~**PE2**: I find AI products/services entertaining.~~ ~~**PE3**: I enjoy using AI products/services.~~	1		

	PE4: I find AI products/services pleasant.			
Perceived Privacy Risk	**PPR1**: It is risky to provide personal information to an AI product/service. **PPR2**: There will be much uncertainty associated with providing personal information to an AI product/service. **PPR3**: There will be much potential loss associated with providing personal information to AI product/service.	3	69.6%	0.7807
Social Presence	**SP1**: There is a sense of human contact with AI. **SP2**: There is a sense of personalness with AI. **SP3**: There is a sense of sociability with AI. **SP4**: There is a sense of human warmth with AI. **SP5**: There is a sense of human sensitivity with AI.	5	70.4	0.8825
Attraction towards AI	~~**AAI1**: Usually, I never hesitate to try new AI product/service~~ ~~**AAI2**: Among my relatives, I am always the first to try new AI product/service~~ ~~**AAI3**: I like to experiment with new AI product/service~~ **AAI4**: Using an AI product/service makes me nervous **AAI5**: I am apprehensive about using an AI Product/Service **AAI6**: I don't use an AI Product/Service because I am not familiar with them **AAI7**: I hesitate to use an AI Product/Service for fear of making mistakes	4	70.2%	0.8583
AI Education	**AIE1**: I can explain how AI Products/services operate.	5	65.4%	0.8650

	AIE2: I can use AI Products/services in different ways. **AIE3**: I can do basic things regarding AI technology. **AIE4**: I can explain general concepts related to AI technology. **AIE5**: I can use AI Products/services effectively.			

As shown in the table just above, we have performed factorial analysis for each construct. The items that have been deleted are the crossed-out items in the table. There have been deleted when it did not meet the conditions set above. The remaining items in the table have final communalities higher than 0.5 and have a correlation higher than 0.6 with the factor. Then, we can see that each construct has a Cronbach's Alpha higher than 0.7, meaning that our scales are reliable.

You will find more information about our factorial analysis in the Appendices 2 to 8.

Chapter 4: Results

In this chapter, we first start to showcase some descriptive statistics concerning our sample and the variables of our conceptual model. After these descriptive statistics, we will perform linear regression in order to further understand the impact of perceived drivers on Perceived Transparency, then we will perform another linear regression to understand the impact of Perceived Transparency on Users' Trust and a final linear regression to understand the impact of Users' Trust on Users' Intention to Use. Finally, we will examine the influence of our moderator variables on our model. Those analyses have been made with Minitab and SAS.

4.1. Descriptive Statistics

Our goal here is to present the variables of our model in order to have a better understanding of the obtained results. You will find below a table showing the variables of our model with some descriptive statistics.

Table 13 Descriptive Statistics of our variables

Statistiques

Variable	N	N*	Moyenne	ErT moyenne	EcTyp	Minimum	Q1	Médiane	Q3	Maximum
Intention_to_use	142	0	5,615	0,105	1,256	1,333	5,000	5,667	7,000	7,000
Perceived_transparency	142	0	3,875	0,107	1,281	1,000	3,000	4,000	5,000	7,000
Trust	142	0	4,313	0,118	1,411	1,000	3,500	4,000	5,500	7,000
Perceived_ease_of_use	142	0	5,3556	0,0985	1,1739	1,0000	5,0000	5,5000	6,0000	7,0000
Perceived_usefulness	142	0	4,998	0,107	1,280	1,000	4,438	5,500	5,813	7,000
Perceived_interpretability	142	0	4,796	0,115	1,367	2,000	4,000	5,000	6,000	7,000
Perceived_security	142	0	3,996	0,122	1,457	1,000	3,000	4,000	5,000	6,000
Perceived_enjoyment	142	0	5,3099	0,0995	1,1861	2,0000	4,0000	6,0000	6,0000	7,0000
Perceived_privacy_risk	142	0	5,160	0,105	1,254	2,000	4,333	5,333	6,000	7,000
Social_presence	142	0	2,646	0,111	1,318	1,000	1,750	2,600	3,450	7,000
Attraction_towards_AI	142	0	3,257	0,125	1,492	1,000	2,000	3,000	4,500	7,000
AI_education	142	0	4,562	0,113	1,343	1,400	3,600	4,800	5,600	7,000

It is important to remember that all these variables are measured with the help of a semantic scale of seven points coming from 1 (Does Not at all Agree) to 7 (Completely Agree), except for the usage of AI Products/services, the usage frequency, money spent for AI Products/services, the age, the gender, the level of education the profession and the income range. We will analyse these variables further in our results.

We will now focus on the seven dimensions of the Drivers (namely the Perceived Ease of Use, the Perceived Enjoyment, the Perceived Usefulness, the Social Presence, the Perceived Security, the Perceived Privacy Risk, and the Interpretability). The Perceived Ease of Use and the Perceived Enjoyment have the highest mean (respectively 5.3556 and 5.3099), followed by the Perceived Privacy Risk (5.160). At this point, we can say that users have a good AI ease of use perception, that they enjoy using AI and that the perceived privacy risk is quite low. After that, we find the Perceived Usefulness and the Perceived Interpretability (respectively 4.998 4.796), meaning that they find it also useful and that they perceive a certain interpretability. Finally, we have the Perceived Security and the Social Presence (respectively 3.996 and 2.646), meaning that the perceived security is a bit below the average, showing a certain reluctance concerning the perception of security. Concerning the Social Presence and his low mean, the indicates that users do not feel a social presence by using AI products/services. Those results induce positive drivers towards users' Trust except maybe for the perceived security and the social presence (meaning that they consider AI as a machine and nothing more).

Then, we will take a look about the results of the moderator variables. The Attraction towards AI products/services is below the mean (3.257), which induces that they are not very attracted to AI products/services, even if the standard deviation is the highest in our table. For the AI Education, at the opposite, we see that the respondents believe that they are quite well-educated concerning AI products/services (4.562).

For the AI products/services usage, 142 respondents have already used AI products/services (92.8%) and only 11 of them have not already used AI products/services – or did use it without knowing it (7.2%). For the Usage Frequency, 55.6% answered using AI products/services more than three times a day, 19.7% once a day, 7.7% between one and three times a week, 9.1% once a week and the rest from once every two months and hardly ever (around 6.5%). We can see that most of our respondents have a strong usage of AI products/services as 75.3% of our respondents used at least once a day an AI product/service.

To finish our descriptive statistics, we will focus more on who are the respondents that answered our survey. Our respondents are composed of 54.2% of women and 45.8% of men. The most present age category is the 19-25 (56.3%), and the most present professions are students (35.9%) and employees (28.9%). What about the Education Level, 57% have a university level and 27.4% have a non-university level of education. Finally, concerning the revenue, 40.14% have revenue lower than 999€ (which is logic due to our 35.9% of students). Nevertheless, 18.3% have revenue between 2000€ and 2499€, 14.8% have revenue of more than 3500€, and 12.7% have revenue between 1500€ and 1999€.

4.2. Correlation

In this part, we performed a correlation analysis between our variables to check that explanatory variables are not too correlated with each other, so we can be sure to avoid multicollinearity problems.

Table 14 Correlation Matrix of the drivers

Corrélation

	Perceived_transparency	Perceived_ease_of_use	Perceived_usefulness	Perceived_interpretability	Perceived_security	Perceived_enjoyment	Perceived_privacy_risk
Perceived_ease_of_use	0,184						
Perceived_usefulness	0,264	0,298					
Perceived_interpretability	0,285	0,331	0,015				
Perceived_security	0,335	0,289	0,435	0,222			
Perceived_enjoyment	0,236	0,267	0,392	0,151	0,358		
Perceived_privacy_risk	-0,166	-0,131	-0,247	-0,145	-0,311	-0,108	
Social_presence	0,304	0,020	0,226	0,037	0,323	0,292	-0,309

First, we see in the table just above that almost all the coefficients inside are positive, except for the Perceived Privacy risk correlation with other dimensions. For the Perceived Privacy risk, these results seem logic as the perceived privacy risk will have a negative influence on the perceived transparency. Then, for the other values, we can see that they are weakly positively correlated between each other (Pearson coefficient lower than 0.4). There is just an exception for the correlation between the Perceived Security and the Perceived Usefulness that are positively correlated (Pearson coefficient between 0.4 and 0.6). With those results, none of the values is strongly correlated with the others, which should prevent us from any multicollinearity problems.

4.3. Hypothesis Validation

In this section, we will determine if the hypotheses of our conceptual model are valid or not. We will also determine the values that have the most impact on the user's trust as well as the impact of this trust on the user's intention to use. To do so, we performed linear regressions of the explanatory variables on the dependant variable.

We will first focus on the relations between the Drivers and the Transparency.

Table 15 Regression Analysis of the drivers on Perceived Transparency

La procédure REG
Modèle : MODEL1
Variable dépendante : Perceived_transparency

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	7	51.70629	7.38661	5.51	<.0001
Erreur	134	179.51246	1.33965		
Total sommes corrigées	141	231.21875			

Root MSE	1.15743	R carré	0.2236
Moyenne dépendante	3.87500	R car. ajust.	0.1831
Coeff Var	29.86917		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	0.72110	0.87118	0.83	0.4093	0
Perceived_usefulness	1	0.13812	0.09161	1.51	0.1340	0.13803
Perceived_ease_of_use	1	0.01461	0.09444	0.15	0.8773	0.01339
Perceived_security	1	0.12647	0.08160	1.55	0.1235	0.14388
Perceived_enjoyment	1	0.03294	0.09510	0.35	0.7296	0.03051
Perceived_privacy_risk	1	0.01819	0.08550	0.21	0.8319	0.01781
Perceived_interpretability	1	0.22117	0.07789	2.84	0.0052	0.23613
Social_presence	1	0.20799	0.08298	2.51	0.0134	0.21407

First, see that the p-value of our model is <.0001, meaning that our model is an explicative model. Then, we can see that all the coefficients have positive values. However, only the **Perceived Interpretability** and the **Social Presence** have a significative impact on transparency (we can draw this conclusion because their p-value is lower than 0.05). We can interpret those coefficients as follows: if we increase by 1 the Perceived Interpretability, the Perceived Transparency will increase by 0.221, and if we increase the Social Presence by 1, the Perceived Transparency will increase by 0.208. Another data that remains important is the Standardized Coefficients (here it is the column "Valeur estimée normalisée"). This coefficient allows us to compare the impact of our different variables. The Perceived Interpretability has a standardized coefficient of 0.236 and the Social Presence has a standardized coefficient of 0.214. We can then conclude that the Perceived Interpretability and the Social Presence have more or less the same impact on the Perceived Transparency. We also see that the R^2 is equal

0.2236, meaning that the different values of our model explain only 22.36% of the variation present in the perceived transparency of the user.

We can now focus on the relation between the Perceived Transparency and the Users' Trust.

Table 16 Regression Analysis of Perceived Transparency on Users' Trust towards AI

La procédure REG
Modèle : MODEL1
Variable dépendante : Trust

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	1	26.35493	26.35493	14.50	0.0002
Erreur	140	254.44965	1.81750		
Total sommes corrigées	141	280.80458			

Root MSE	1.34815	R carré	0.0939
Moyenne dépendante	4.31338	R car. ajust.	0.0874
Coeff Var	31.25498		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	3.00513	0.36170	8.31	<.0001	0
Perceived_transparency	1	0.33761	0.08866	3.81	0.0002	0.30636

First, see that the p-value of our model is 0.0002, meaning that our model is an explicative model. Then, we can see that the coefficient of the Perceived Transparency is positive, and that it has a significative impact on Users' Trust towards AI (we can draw this conclusion because their p-value is lower than 0.05). We can interpret the coefficient of Perceived Transparency as follows: if we increase by 1 the Perceived Transparency, the Users' Trust towards AI will increase by 0.337. As before, we will also see the standardized coefficient, which will allow us to compare the impact of our different variables. This coefficient for the Perceived Transparency equals 0.306 and represents the impact of Perceived Transparency. We also see that the R^2 is equal 0.0939, meaning that the different values of our model explain only 9.39% of the variation present in the Users' Trust towards AI. The R^2 is very low, and with the p-value of the model lower than 0.05, we can induce that Transparency has a low impact on Users' Trust towards AI.

We can now focus on the relation between the Users' Trust towards AI and the Users' Intention to Use AI Products/services.

Table 17 Regression Analysis of Users' Trust towards AI on Users' Intention to Use AI

La procédure REG
Modèle : MODEL1
Variable dépendante : Intention_to_use

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	1	9.61644	9.61644	6.33	0.0130
Erreur	140	212.67151	1.51908		
Total sommes corrigées	141	222.28795			

Root MSE	1.23251	R carré	0.0433
Moyenne dépendante	5.61502	R car. ajust.	0.0364
Coeff Var	21.95023		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	4.81680	0.33369	14.44	<.0001	0
Trust	1	0.18506	0.07355	2.52	0.0130	0.20799

First, see that the p-value of our model is <.0130 (and so, lower than 0.05), meaning that our model is an explicative model. Then, we can see that the coefficient of the Users' Trust towards AI is positive, and that it has a significative impact on Users' Intention to Use AI Products/services (we can draw this conclusion because their p-value is lower than 0.05). We can interpret the coefficient of Users' Trust towards AI is positive as follows: if we increase by 1 the Users' Trust towards AI is positive, the Users' Intention to Use AI Products/services will increase by 0.185. As before, we will also see the standardized coefficient, which will allow us to compare the impact of our different variables. This coefficient for the Perceived Transparency equals 0.208 and represents the impact of Users' Trust towards AI. We also see that the R^2 is equal 0.0433, meaning that the different values of our model explain only 4.33% of the variation present in the Users' Trust towards AI. The R^2 is very low, meaning that Users' Trust towards AI explains 4.33% of the variation in the Users' Intention to Use AI Products/services. This is a relatively small number, and it is obviously understood that other variables need to be added to understand better the variations in Users' Intention to Use AI Products/services.

4.4. Moderating Variables

Due to the results of our regression analysis, we are not able to check our moderating variables. Indeed, as the Perceived Transparency has no significative impact on Users' Trust towards AI and that Users' Trust towards AI has no significative impact on Users' Intention. As our moderating variables acted between those two relations that are not significative, it would not make sense to analyse them.

In this part, we will determine the effect of moderator variables on our variables. We will first explain what moderator variables are. A moderator is a variable which will alter the strength of the relation between two other variables (an independent variable and a dependent variable). This relation's strength will increase or decrease according to the value of the moderator. We will analyse seven moderators, namely the Attraction towards AI Products/services, the AI Education, the Age, the Gender, the profession, the education level, and the revenue.

To study those moderating effects, we performed multiple regressions. Each regression has an equation including the dependent variable, the studied independent variable, and the moderator variable. By analysing the coefficient of this last variable, we will there be able to determine if there is a moderating effect or not. You can find the details of our analysis in the Appendices.

4.4.1. Perceived Transparency and User's Trust – Moderating Effects

No moderating effect has been discovered during our analysis. We found out that all the p-values were higher than 0.1, making them not significative.

4.4.2. Users' Trust and Intention to Use – Moderating Effects

Table 18 Summary of moderating effects of the relation between Users' Trust towards AI and Users' Intention to Use

Variable	Moderator	Coefficients	p-value	R-Square before adding the moderator	R-Square after adding the moderator
Users' Trust	Profession	X=0.0005 Z=-0.4868 XZ=0.0762	0.9951 0.0001 0.0037	0.1215	0.1736
	Revenue	X=0.0661 Z=-0.2627 XZ=0.0609	0.5115 0.1118 0.0871	0.0434	0.0636

X represents the Users' Trust; Z represents the moderating variable and XZ the moderating effect.

First, we see in the table that only the profession and the revenue have a significative moderating effect (at a threshold of 10%, we respectively have a p-value = 0.0037 for the profession and a p-value = 0.0871 for the revenue) on the relation Users' Trust towards AI – Users' Intention to Use AI. The coefficients of those moderators are significantly positive.

For the **Profession**, the Adjusted R-Square comes from comes from 0.1215 to 0.1736 by adding this moderating variable. The Z in our table represents the Users' Trust towards AI and the coefficient XZ is computed for the Users' Trust with the moderator Profession. We will interpret this in order to make it more understandable. Furthermore, we can see in the table below that only Students and People with a job have a significative impact on Users' Intention to Use AI (p-value respectively is 0.0011 and 0.0496) but not for People with any job (p-value = 0.1429). We can conclude here that being a student will have a negative influence on their Intention to Use AI (with a value -0.4907), and at the opposite, that People with a job will have a positive influence on their Intention to Use AI (with a value 0.2922).

Variable	Moderator	Coefficients	p-value	R-Square before adding the moderator	R-Square after adding the moderator
Users' Trust	No Job	X=0.1364 Z=-1.8387 XZ=0.2652	0.0938 0.0314 0.1429	0.1215	0.0911
	Students	X=0.3648 Z=2.5918 XZ=-0.4907	<0.0001 0.0001 0.0011	0.1215	0.1482
	With a Job	X=0.0606 Z=-1.4159 XZ=0.2922	0.5414 0.0358 0.0496	0.1215	0.0760

X represents the Users' Trust; Z represents the moderating variable and XZ the moderating effect.

For the **Revenue**, the Adjusted R-Square comes from comes from 0.0434 to 0.0636 by adding this moderating variable. The Z in our table represents the Users' Trust toward AI and the coefficient XZ is computed for the Users' Trust with the moderator Revenue. We will interpret this to make it more understandable. Furthermore, we can see in the table below that only Low Revenue and Medium Revenue people have a significative impact Users' Intention to Use AI (p-value respectively is 0.0215 and 0.0343) but not for people with high revenue (p-value = 0.8873). We can conclude here that people with low revenue have a negative influence on users' Intention to Use AI (with a value -0.335), and that people with medium revenue has a positive influence on Users' Intention to Use AI (with a value 0.3183).

Table 19 Summary of moderating effects of the relation between Users' Trust towards AI and Users' Intention to Use - Details of Revenue

Variable	Moderator	Coefficients	p-value	R-Square before adding the moderator	R-Square after adding the moderator
Users' Trust	Low Revenue	X=0.35 Z=1.76 XZ=-0.335	0.0007 0.008 0.0215	0.0434	0.0943
	Medium Revenue	X=0.052 Z=-1.9323 XZ=0.3183	0.5591 0.0042 0.0343	0.0434	0.1222
	High Revenue	X=0.0803 Z=0.5017 XZ=-0.0301	0.0318 0.6250 0.8873	0.0434	0.0563

X represents the Users' Trust; Z represents the moderating variable and XZ the moderating effect.

Chapter 5: Discussion

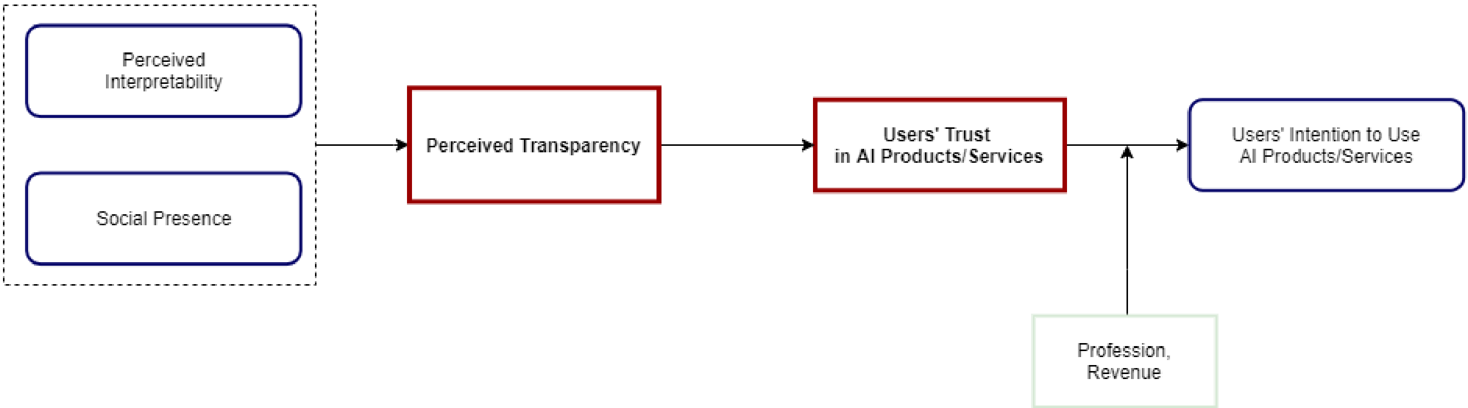
First, 7.2% (11 on 153) of our respondents, a number that is very interesting, truly believe that they do not use services or products with AI embedded. This information remains crucial as we are now surrounded by AI (for instance in social media or in our mailbox), leading us to believe that those people simply have a very little idea of the form that AI can take (through recommendations, anti-spam filters, …). We dropped that data as the survey ended if they said that they don't use an AI product/service, leaving us with 142 valid answers. For the repartitions, 54.2% were women and 45.8 were men. Also, 56.3% are from 19 to 25 years old, which is biased because it is the main target if the survey is sent through social media, and it is the same for the education level as 57% have a university level and that 36% are students. 55.6% of our respondents use AI more than 3 times a day, and 20% only once a week. This means that almost 75% of our respondents use AI products/services at least once a day, which is well representative. Therefore, the question of transparency remains an important concept to study because we are talking about a daily usage. About the money spent, 28.1% of our respondents answered spending 0€ for AI products/services, 21.1% respondents answered having no idea, and 21% answered spending between 10 and 29.99€. As we can see, people are ready to pay for some specific AI usages, and it is good to know for products and services providers.

We started our empirical part with a factorial analysis, we have been able to check the reliability of our scales. We dropped some items, but we could keep all our variables. Then we continued by performing a descriptive analysis in order to have a better comprehension of our sample. We saw that people have quite a good perceived Ease of Use and Perceived Enjoyment, as they have the highest mean. It induces that people see the ease of use concerning AI and that they enjoy using AI Products/services. The Perceived Privacy Risk has also a high mean, meaning that they are quite confident about the privacy risk. After that, they had lower mean for the Perceived Usefulness and the Perceived Interpretability (4.99 and 4.79). They perceive the usefulness, and they can interpret what the AI returns. At the opposite, we had low means concerning the Perceived Security and the Social Presence (3.99 and 2.64); our respondents have a problem with the security of AI products/service and then, a reluctance towards those products/services. For the Social Presence, it induces that users do not feel a social presence by using AI products/services.

After that, our correlation matrix insured us that any problems of multicollinearity should be avoided. Thanks to that confirmation, we have been able to launch our regressions analysis in order to evaluate the impact of our different drivers on the Perceived Transparency; then the impact of the Perceived Transparency on the Users' Trust in AI Products/Services and finally the impact of the Users' Trust in AI Products/Services on the Users' Intention to Use AI Products/Services.

A summary of our results is presented in the figure below, with the hypotheses that have been validated.

Figure 16 Conceptual Model - Summary of our analysis



Our first regression analysis showed us that our model is explicative (with a model p-value >.0001) and demonstrated us that the **Perceived Interpretability** (with a value = 0.221 and a p-value = 0.0052) and the **Social Presence** (with a value = 0.207 and a p-value = 0.0134) have a positive and significative impact on Perceived Transparency, and that their impact is the same. Also, our model explains only 22.36% of the variation present in the Perceived Transparency of users. We can interpret the results as the more you have Social Presence and Perceived Interpretability, the more users will perceive Transparency in their AI products/services usage. With our first regression analysis, we have been able to demonstrate that two of our drivers have a significant impact on perceived transparency, namely the social presence and the perceived interpretability. Concerning the perceived interpretability, it is not surprising; it means that a perceived interpretability will have a positive impact on perceived transparency. As we needed to create our own items to measure the interpretability, we see that our result is significative and could be taken into consideration. Concerning the social presence, it means that social presence will have a positive impact on perceived transparency. In other words, we demonstrated in our thesis that a good interpretability (of the results, the advice and the predictions made by the AI service/product) and social presence will have a positive impact on perceived transparency. Our recommendations will be to make your AI the most look-alike possible (with human voices, friendly answers, consideration for the user…) and allow the best tools to interpret the outcomes (with graphics, summaries of the decisions/actions…).

Then our next regression analysis showed us that our model is explicative (with a model p-value = 0.0002) and demonstrated that Perceived Transparency has a significant impact on Users’ Trust (with a value = 0.3376 and a p-value = 0.0002). Perceived Transparency has then a positive impact on Users’ Trust towards AI. Our model explains only 9.39% of the variation present in the Perceived Transparency of users and can be explained because we only used Perceived Transparency to measure the impact of Intention to Use only. At this point, we can say that Transparency has a significative and positive impact on Trust, but it is probably not the main variable offering the biggest impact on Trust. Nevertheless, Transparency should be considered as it has a positive impact, meaning that a lack of Transparency would lead to a negative impact on Trust. We have been able to demonstrate that Perceived Transparency has a significant impact on Users’ Trust towards AI. Our hypothesis is thus validated as we can confirm that there is a link between Transparency and the Users’ Trust towards AI. Nevertheless, our model explains only 9.39% of the variation, but that can be easily explained because transparency is not the only variable having an impact on Trust by far. Thanks to our analysis, we don’t only see a significative impact of Transparency but a positive and significative impact, meaning that Perceived Transparency impact positively Users’ Trust, validating our hypothesis. For AI products/services providers, Transparency is an important variable that must be considered if they want to gain users’ trust towards the products/services. Indeed, this is not an easy task as it can be difficult to be fully truly transparent without being too technic in the outputs offered (like a report, a graph…).

Our final regression analysis showed us that our model is explicative (with a model p-value 0.0130) and also demonstrated that Users’ Trust towards AI also has a significant impact on Users’ Intention to Use AI (with a value = 0.1850 and a p-value=0.013). Users’ Trust towards AI has then a positive impact on Users’ Intention to Use AI. Our model explains only 4.33% of the variation in Users’ Intention to Use AI and can be explained because we only used Users’ Trust to measure the impact of Intention to Use only. At this point, we can say that

Users' Trust has a significative and positive impact on Trust, but it is probably not the main variable impacting the most the Users' Intention to Use. Nevertheless, Transparency should be considered as it has a positive impact, meaning that a lack of Users' Trust would lead to a negative impact on the Users' Intention to Use AI, which seems very logical. We have been able to demonstrate that Users' Trust towards AI has a significant impact on Users' Intention to use AI Products/Services. Our hypothesis is then also validated, as our regression presented a significant and positive impact of the Users' Trust on the Users' Intention to Use AI products/services. Also, the model explains only 4.33% of the variation and can also be explained because there are probably other variables that have an impact on Users' Intention to Use AI. Therefore, as our hypothesis is validated, we can say that Transparency has a positive impact on Users' Trust towards AI, which has a positive impact on Users' Intention to Use AI. The significative impact might be not that important but there is remaining information to consider in order to gain the best possible trust from our users.

We found out that our moderators applied between Perceived Transparency and Users' Trust towards AI did not have significative impact on the relation. Therefore, we cannot validate those hypotheses. Concerning the moderators applied between Users' Trust towards AI and Users' Intention to Use AI Products/Services, two of our moderators had a significative impact on the relation: The profession and the revenue.

Concerning the profession, we found out that people with a job will have a positive influence on the relation, while student people will have a negative influence on the relation. By going further in our analysis, we saw that being a student will weaken the relation between Users' Trust towards AI and Users' Intention to Use AI products/services (-0.4907, meaning that being a student negatively influence the relation) and that people with a job, at the opposite, will reinforce this relation (0.2922, meaning that having a job positively influence the relation).

Concerning the revenue, we found out that having a low revenue has a negative influence on the relation, while having a medium revenue will have a positive influence on the relation. These results can be interpreted due to the revenue and the idea that AI products/services can have an important cost, and it is the same for students (which is linked with the revenue with revenue <999€ per month for all of them). Nevertheless, this does not allow us to draw a conclusion with the transparency as those moderators are only significative between the relation of Users' Trust AI and Users' Intention to Use AI.

For the revenue, Low and Medium revenue have an impact. Low Revenue has a negative and significative impact on the Users' Intention to Use AI, and Medium Revenue has a positive and significative impact on the Users' Intention to Use AI. Having a medium revenue will then reinforce the relation between Users' Trust towards AI and Users' Intention to Use AI products/services, while having a low revenue will weaken this relation.

Chapter 6: Conclusion

The goal of this thesis was to discover if there was an impact of Transparency on Users' Trust towards AI, and thus on their Intention to Use. To do so, we started to make a literature review on the topics surrounding our theme: Customers and the AI (the perception of AI by customers and the consumers' trust), the AI in the business field (with the interpretability and the explanations) and finally, the transparency. After this important step, we have been able to create our conceptual model and formulate our hypotheses, and create our survey in French, shared on social media. We present here our main results with managerial recommendations.

The second part consisted of a quantitative analysis. To do this, we used the information collected during our literary review to build our survey, which was sent via social networks. In the end, we collected 153 answers, allowing us to better understand the perception that an AI user has, as well as the impact that perceived transparency could have user's trust.

To conclude, through this work, we tried to define the impact that transparency could have on users' trust. Thanks to our quantitative analysis, we have been able to validate some of our hypothesis, showing a positive and significative impact of Perceived Transparency on Users' Trust towards AI and a positive and significative impact of Users' Trust towards AI on Users' Intention to Use AI products/services. Indeed, we saw the importance of AI transparency in the service world (Arnold et al., 2019) and can lead to negative outcomes in the eyes of users. As transparency allows a better comprehension, it is important to build an AI product/service around transparency in order to gain users' trust towards the service/product. Furthermore, to be trustworthy, users want AI systems that are transparent and explainable (IBM – 2018), showing a real desire from users as the actual research around transparency are focussing more and more on interpretability, making AI even more reliable. In the business field, we have already seen some model that have been created to interpret at best what is inside the AI black box, allowing experts but also marketing and business parts to understand the model outcomes (Ribeiro and al., 2016). This interpretability should be offered as a new variable on transparency, and we lacked research with interpretability in a quantitative way for our literature review.

Transparency is therefore a variable that must be considered for AI products/services providers as it is more and more required by users. Indeed, our results show that transparency plays a role in Users' Trust towards AI, meaning that if they perceive a transparency in the service or product, users will be more inclined to trust and therefore to use AI product/service.

Furthermore, transparency is a subject that is more and more studied at this point, and it is important to go further in that way. Besides transparency, interpretability can be presented as a tool of transparency as it allows to explain the functioning or the outcomes of AI. With those results, we showed that an impact exists, and that implies that further research can be led to increase the understanding of transparency on trust and on their intention to use.

Nevertheless, we have not been able to draw some conclusion about the AI Education and his influence on trust. We think that it could be interesting to go further, as we saw in our literary review that people with low knowledge about AI have the biggest lack of trust (PEGA – 2019). Unfortunately, our variable AI Education was not significative, and we cannot draw any conclusions at this point. We develop this point in the further in the conclusion.

Limitations

We can put forward some limitations concerning our thesis. First, Perceived interpretability has been reviewed in the literature but not in research like we are doing. Therefore, we have not been able to find measures made according to that topic. As interpretability remains an important topic in the world of AI and their perceived transparency, we created our items scales to be able to evaluate this concept. Perceived Interpretability must be studied in greater depth to allow researchers to go deeper into the concept of Transparency.

Then, we can see afterwards a certain limitation in our data. The survey was not easy for people with low AI-knowledge, leading to probable misunderstanding and thus distorting the data. With our filter question, we needed people who have at least a minimum of AI products/services usage. Just after this filter, we tried to show them that they use AI services (for instance, just by being on Facebook or a mailbox, they are using some AI services). Nevertheless, AI products/services remain really abstract for most users, leading to misunderstanding of what AI is and what AI can do with services and products. This abstract aspect may play an important role in the quality of our data. The size of our data also remains very small (around 150 respondents), and it could be more effective to perform on a greater sample. Also, our sample mainly contains young respondents, so we cannot consider our results as being explainable for all the populations, but only for younger people.

Finally, one of our hypotheses was about the AI Education as being probably a moderator variable. Surprisingly, our results demonstrated that this hypothesis is false, and that AI Education has not significative impact. However, this result could be wrong as we let the opportunity to the respondents to estimate their AI Education. Indeed, it would be more relevant to evaluate their AI Education through tests to be sure that they know what they are talking about.

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Appendix 1 : Questionnaire

Bonjour à toutes et à tous,

Dans le cadre de mon mémoire à finalité spécialisée en Data Science à l'Université de Namur, je réalise une enquête sur le domaine de l'intelligence artificielle (AI).

L'intelligence artificielle prend une place de plus en plus importante dans notre société et dans notre façon de consommer au quotidien, et présente donc une croissance exponentielle. Pour ce faire, je souhaiterais connaître un peu mieux à quel point l'intelligence artificielle peut avoir une influence sur le marketing, ainsi que sur les consommateurs.

L'enquête dure entre 5 et 10 minutes. Vous pouvez participer à l'enquête que vous soyez un consommateur d'IA ou non. Les réponses sont complètement anonymes.

Je vous remercie d'avance pour votre participation, qui me sera d'une aide très précieuse !

Si vous avez des questions ou une remarque, n'hésitez pas à me contacter via mon adresse mail thomas.keiser@student.unamur.be.

Partie 1 : Consommation de produits ou services avec de l'IA

Q1 : Consommez-vous des produits/services avec de l'IA ? (Plus précisément, avez-vous déjà utilisé des produits/services avec de l'IA au cours du dernier mois ?)

- Oui
- Non

Question filtre (dans le cas où la personne répond non à l'utilisation de produits ou services avec de l'IA) :

Q2 : Avez-vous déjà utilisé un service dans la liste ci-dessous ?

- Recommandations pour du shopping en ligne (Amazon ou tout autre shopping en ligne)
- Un assistant virtuel (Siri, Alexa, Ok Google, …)
- Des assistants virtuels (chatbots en tant que support par exemple)
- Des news recommandés par Facebook
- Des recommandations de recherches du navigateur (Google, Firefox, Safari, …)
- Des filtres de spam d'e-mail
- De la reconnaissance faciale
- Aucun des exemples cités ci-dessus

→ SI une seule des case (excepté la dernière) est sélectionnée :

L'IA se retrouve de plus en plus dans les services et les produits que nous utilisons au quotidien. En effet, dans tous les services qui ont été présentés dans la question précédente, on retrouve une intelligence artificielle embarquée, souvent sous forme de prédictions (avec des recommandations, des filtres, …) où sous forme de décision (la reconnaissance faciale qui va débloquer son propre téléphone). Il n'est pas impossible d'utiliser des produits ou des services avec de l'intelligence artificielle embarquée sans même le savoir ! Ce n'est pas un problème, vous avez maintenant un peu plus de vision quant à ce à quoi peut ressembler une IA.

→ SI « Aucun des exemples cités ci-dessus » n'est sélectionné (cas où le répondant n'a vraiment jamais utilisé de produits/services avec de l'IA) :

Merci pour votre participation.

Q3 : À quelle fréquence pensez-vous utiliser un (ou plusieurs) produit(s)/service(s) avec de l'IA ?

- Plus de 3 fois par jour
- Une fois par jour
- 2 à 3 fois par semaine
- Une fois par semaine
- Une fois tous les 2 mois
- Une fois par an
- Moins d'une fois par an
- Presque jamais

Q4 : Combien dépensez-vous dans des produits/services avec de l'IA par mois en moyenne ? (par exemple via des abonnements ou via des achats ponctuels)

- 0 €
- Entre 0,01 et 0,99 €
- Entre 1 et 4,99 €
- Entre 5 et 9,99 €
- Entre 10 et 19,99 €
- Entre 20 et 29,99 €
- Entre 30 et 39,99 €
- Entre 40 et 49,99 €
- Entre 50 et 59,99 €
- Entre 60 et 69,99 €
- Entre 70 et 79,99 €
- Entre 80 et 89,99 €
- Entre 90 et 99,99 €
- Plus de 100 €

Q5 : Sur une échelle de 1 à 7, "1" étant pas du tout d'accord et "7 " tout à fait d'accord, veuillez indiquer dans quelle mesure vous êtes d'accord avec les propositions suivantes :

	1. Pas du tout d'accord	2	3	4	5	6	7. Tout à fait d'accord
Il est probable que j'utilise des produits/services d'IA à l'avenir.							
J'ai l'intention d'utiliser fréquemment les produits/services d'IA.							
Je pense continuer à utiliser les produits/services d'IA à l'avenir.							

Partie 2 : Valeurs perçues d'une IA

Q6 : Sur une échelle de 1 à 7, "1" étant pas du tout d'accord et "7 " tout à fait d'accord, veuillez indiquer dans quelle mesure vous êtes d'accord avec les propositions suivantes :

	1. Pas du tout d'accord	2	3	4	5	6	7. Tout à fait d'accord
Les produits/services d'IA interagissent avec moi de manière compétente et efficace.							
Les produits/services d'IA remplissent très bien tous leurs rôles.							
Dans l'ensemble, les produits/services d'IA sont capables et compétents.							
Les produits/services d'IA sont honnêtes avec moi.							
Je qualifierais les produits/services d'IA comme étant honnêtes.							
Les produits/services d'IA sont sincères et authentiques.							

Q7 : Sur une échelle de 1 à 7, "1" étant pas du tout d'accord et "7 " tout à fait d'accord, veuillez indiquer dans quelle mesure vous êtes d'accord avec les propositions suivantes :

	1. Pas du tout d'accord	2	3	4	5	6	7. Tout à fait d'accord
Je pense que l'utilisation de produits/services d'IA améliorerait l'efficacité lors de ma consommation.							
Je pense que l'utilisation de produits/services d'IA me serait utile.							
Je pense que l'utilisation de produits/services d'IA dans ma consommation augmenterait ma productivité.							

Globalement, je trouve les produits/services de l'IA utiles à ma consommation.							

Q8 : Sur une échelle de 1 à 7, "1" étant pas du tout d'accord et "7 " tout à fait d'accord, veuillez indiquer dans quelle mesure vous êtes d'accord avec les propositions suivantes :

	1. Pas du tout d'accord	2	3	4	5	6	7. Tout à fait d'accord
L'interaction avec les produits/services d'IA ne nécessiterait pas un effort mental important.							
Je pense que travailler avec des produits/services d'IA est aussi facile que de travailler avec des humains.							
Apprendre à utiliser les produits/services de l'IA serait facile pour moi.							
Globalement, je trouve les produits/services d'AI faciles à utiliser.							
Le résultat (conseils, prédictions ou décisions) du produit/service d'IA est clair pour moi.							
Je peux facilement interpréter le résultat (conseils, prédictions ou décisions) du produit/service d'IA et pourquoi il a produit un tel résultat.							
Je peux facilement expliquer le résultat (conseils, prédictions ou décisions) du produit/service d'IA et pourquoi il a produit un tel résultat.							

Q9 : Sur une échelle de 1 à 7, "1" étant pas du tout d'accord et "7 " tout à fait d'accord, veuillez indiquer dans quelle mesure vous êtes d'accord avec les propositions suivantes :

	1. Pas du tout d'accord	2	3	4	5	6	7. Tout à fait d'accord
Je perçois les produits/services d'IA comme une technologie sûre.							
Je perçois les informations relatives à l'interaction entre l'utilisateur et les produits/services d'IA comme sûres.							
Les informations que j'ai fournies lors de ma précédente interaction avec IA Produits/Services sont utiles pour les interactions ultérieures.							
Je ne crains pas les invasions de hackers dans les produits/services d'IA.							

Q10 : Sur une échelle de 1 à 7, "1" étant pas du tout d'accord et "7 " tout à fait d'accord, veuillez indiquer dans quelle mesure vous êtes d'accord avec les propositions suivantes :

	1. Pas du tout d'accord	2	3	4	5	6	7. Tout à fait d'accord
Je trouve les produits/services de l'IA intéressants.							
Je trouve les produits/services de l'IA divertissants.							
J'aime utiliser les produits/services de l'IA.							
Je trouve les produits/services de l'IA agréable à utiliser.							

Q11 : Sur une échelle de 1 à 7, "1" étant pas du tout d'accord et "7 " tout à fait d'accord, veuillez indiquer dans quelle mesure vous êtes d'accord avec les propositions suivantes :

	1. Pas du tout d'accord	2	3	4	5	6	7. Tout à fait d'accord
Il est risqué de fournir des informations personnelles à un produit/service d'IA.							
Il y a beaucoup d'incertitude associée à la fourniture d'informations personnelles à un produit/service d'IA.							
Il y aura beaucoup de pertes potentielles associées à la fourniture d'informations personnelles au produit/service IA.							

Q12 : Sur une échelle de 1 à 7, "1" étant pas du tout d'accord et "7 " tout à fait d'accord, veuillez indiquer dans quelle mesure vous êtes d'accord avec les propositions suivantes :

	1. Pas du tout d’accord	2	3	4	5	6	7. Tout à fait d’accord
Il y a un sentiment de contact humain avec l'IA.							
Il y a un sentiment de caractère personnel avec l'IA.							
Il y a un sentiment de sociabilité avec l'IA.							
Il y a un sentiment de chaleur humaine avec l'IA.							
Il y a un sentiment de sensibilité humaine avec l'IA.							

Partie 3 : Compréhension, transparence et interprétabilité d’une IA

Q13 : Sur une échelle de 1 à 7, "1" étant pas du tout d'accord et "7 " tout à fait d'accord, veuillez indiquer dans quelle mesure vous êtes d'accord avec les propositions suivantes :

	1. Pas du tout d’accord	2	3	4	5	6	7. Tout à fait d’accord
En général, je n'hésite jamais à essayer un nouveau produit/service d'IA.							
Parmi mes proches, je suis toujours le premier à essayer un nouveau produit/service d'IA.							
J'aime expérimenter de nouveaux produits/services d'intelligence artificielle.							
L'utilisation d'un produit/service d'IA me rend nerveux							
J'appréhende l'utilisation d'un produit/service d'IA.							
Je n'utilise pas de produit/service d'IA parce que je ne les connais pas.							
J’hésite à utiliser des produits/services IA par peur de faire des erreurs							

Q14 : Sur une échelle de 1 à 7, "1" étant pas du tout d'accord et "7 " tout à fait d'accord, veuillez indiquer dans quelle mesure vous êtes d'accord avec les propositions suivantes :

	1. Pas du tout d’accord	2	3	4	5	6	7. Tout à fait d’accord
Je peux expliquer le fonctionnement des produits/services d'IA.							

Je peux utiliser les produits/services d'IA de différentes manières.							
Je peux faire des choses de base concernant la technologie de l'IA.							
Je peux expliquer des concepts généraux liés à la technologie de l'IA.							
Je peux utiliser efficacement les produits/services d'IA.							

Q15 : Transparence

	1. Pas du tout d'accord	2	3	4	5	6	7. Tout à fait d'accord
Le produit/service d'IA me permet de suivre mes activités.							
Le produit/service d'IA fournit des informations sur ses décisions et ses actions.							
Le produit/service d'IA fournit des informations sur ses règles et règlements.							
Le produit/service d'IA diffuse de l'information sur sa propre performance.							
Globalement, le produit/service IA a une transparence accrue sur ce qu'il fait.							

Partie 4 : Partie démographique

Q16 : Vous êtes un.e…

- Homme
- Femme

Q17 : Dans quelle tranche d'âge vous situez-vous ?

- 18 ans ou moins
- 19-25
- 26-30
- 31-35
- 36-40
- 41-45
- 46-50
- 51-55
- 56-60
- Plus de 60 ans

Q18 : Quel est votre niveau d'éducation ?

- Primaire
- Secondaire inférieur

- Secondaire supérieur
- Supérieur non universitaire
- Universitaire
- Doctorat
- Autre

Q19 : Quelle est votre profession actuelle ?

- Etudiant.e
- Indépendant.e
- Cadre
- Employé.e
- Ouvrier(ère)
- Profession libérale
- Pensionné.e
- Chercheur d'emploi
- Personne au foyer
- Autre (précisez)

Q20 : Dans quelle tranche de revenu vous situez-vous ? (revenu mensuel)

- Moins de 1499 €
- Entre 1500 et 1999 €
- Entre 2000 et 2499 €
- Entre 2500 et 2999 €
- Entre 3000 et 3499 €
- Plus de 3500 €

Merci d’avoir participé à cette enquête, votre aide m’est très précieuse !

Appendix 2: Factorial Analysis for the construct Intention to Use

Alpha de Cronbach

Alpha
0,8570

Saturations de facteurs et communalités sans rotations

Variable	Facteur1	Communalité
INTU1	0,849	0,721
INTU2	0,891	0,794
INTU3	0,912	0,831
Variance	2,3463	2,3463
% variance	0,782	0,782

Coefficients des scores de facteur

Variable	Facteur1
INTU1	0,362
INTU2	0,380
INTU3	0,389

The construct corresponding to the respondents' Intention to Use AI products/services contains 3 items. We make a factorial analysis, and the results are presented just above. With the above results, we can already notice that the commonalities are higher than 0.6 for each item (with the lowest one at 0.72) with a correlation higher than 0.75 for each item. Also, we can note that the factors are higher than 0.6. We can therefore keep the 3 items, representing our scale by those 3 items.

The Cronbach's Alpha is way higher than 0.7 (here it is 0.857), so we can confirm that those 3 items measure well one and only one construct, the Intention to Use AI Product/Services of the users.

The cumulative percentage variance is 74.4%.

Appendix 3: Factorial Analysis for the construct Trust

Alpha de Cronbach

Alpha
0,8055

Saturations de facteurs et communalités sans rotations

Variable	Facteur1	Communalité
TRU4	0,915	0,837
TRU5	0,915	0,837
Variance	1,6746	1,6746
% variance	0,837	0,837

Coefficients des scores de facteur

Variable	Facteur1
TRU4	0,546
TRU5	0,546

The construct corresponding to the respondents' Trust AI products/services contains 6 items. We make a factorial analysis, and only the items TRU4 and TRU5 have commonalities higher than 0.5, we delete then the other items and we start again the factorial analysis (the results are presented just above). As we can see, the commonalities are higher than 0.6 (they both have a commonality of 0.837). Also, we can note that the factors are higher than 0.6. Our scale is then represented by 2 items.

The Cronbach's Alpha is way higher than 0.7 (here it is 0.8055). This means that the 2 items measure a unidimensional construct: the Trust.

The cumulative percentage variance is 83.7%

Appendix 4: Factorial Analysis for the construct Perceived Transparency

Alpha de Cronbach

Alpha
0,7715

Saturations de facteurs et communalités sans rotations

Variable	Facteur1	Communalité
TRA2	0,743	0,552
TRA3	0,771	0,595
TRA4	0,765	0,585
TRA5	0,803	0,645
Variance	2,3771	2,3771
% variance	0,594	0,594

Coefficients des scores de facteur

Variable	Facteur1
TRA2	0,313
TRA3	0,324
TRA4	0,322
TRA5	0,338

The construct corresponding to the respondents' Perceived Transparency of AI products/services contains 5 items. We make a factorial analysis, and the items TRA2, TRA3, TRA4 and TRA5 have commonalities higher than 0.5. We then decide to delete the last item (TRA1) and we start again the factorial analysis (the results are presented just above). As we can see, the commonalities are a bit higher than 0.6 (respectively 0.552, 0.595, 0.585 and 0.645). Also, we can note that the factors are higher than 0.6. Our scale is then represented by 4 items.

The Cronbach's Alpha is higher than 0.7 (here it is 0.7715 for transparency). This means that the 3 items measure a unidimensional construct: the perceived transparency.

The cumulative percentage variance is 59.4%

Appendix 5: Factorial Analysis for the construct Drivers

PART 1

Saturations de facteurs et communalités avec rotations

Rotation varimax

Variable	Facteur1	Facteur2	Facteur3	Facteur4	Facteur5	Facteur6	Facteur7	Communalité
PEU1	0,144	0,069	-0,006	0,126	0,168	0,150	-0,726	0,618
PEU2	0,048	0,300	-0,592	0,073	-0,167	-0,127	-0,200	0,532
PEU3	0,294	-0,090	-0,100	-0,099	-0,810	-0,076	0,008	0,777
PEU4	0,108	0,068	-0,138	0,077	-0,859	-0,028	-0,095	0,789
PE1	0,456	0,119	-0,120	-0,245	-0,002	-0,582	-0,143	0,655
PE2	0,434	0,141	-0,110	-0,053	-0,133	-0,491	0,220	0,530
PE3	0,659	0,160	-0,155	-0,024	-0,157	-0,526	-0,057	0,790
PE4	0,262	0,187	-0,148	0,039	-0,112	-0,784	-0,083	0,761
PU1	0,774	0,094	-0,162	-0,073	-0,096	-0,086	0,039	0,658
PU2	0,805	-0,014	-0,119	-0,067	-0,086	-0,121	0,033	0,689
PU3	0,769	0,159	-0,186	-0,071	-0,097	-0,036	0,027	0,667
PU4	0,793	0,039	-0,079	-0,096	-0,047	-0,223	-0,110	0,709
SP1	0,052	0,808	-0,010	-0,128	0,119	-0,152	-0,140	0,728
SP2	0,058	0,710	-0,048	-0,094	-0,071	-0,052	-0,283	0,606
SP3	0,098	0,826	-0,224	-0,039	0,115	-0,097	0,153	0,790
SP4	0,076	0,888	-0,131	-0,131	-0,040	-0,030	0,082	0,838
SP5	0,119	0,819	-0,185	-0,116	-0,118	-0,074	0,131	0,768
PS1	0,237	0,094	-0,765	-0,153	-0,098	-0,189	0,095	0,727
PS2	0,226	0,157	-0,807	-0,120	-0,079	-0,136	-0,119	0,780
PS3	0,199	0,113	-0,330	0,024	-0,112	-0,296	-0,165	0,289
PS4	0,201	0,085	-0,473	-0,256	-0,051	0,269	-0,176	0,443
PPR1	-0,242	-0,074	0,061	0,800	0,106	-0,077	0,181	0,757
PPR2	0,012	-0,105	0,239	0,809	0,129	0,143	-0,126	0,776
PPR3	-0,090	-0,277	-0,013	0,759	-0,121	0,034	0,017	0,677
I1	0,111	0,029	-0,113	-0,181	-0,500	-0,267	-0,438	0,572
I2	-0,177	-0,061	-0,211	-0,141	-0,387	-0,195	-0,681	0,751
I3	-0,143	-0,039	-0,222	-0,139	-0,350	-0,163	-0,591	0,588
Variance	3,8409	3,6871	2,3728	2,2288	2,1759	2,0090	1,9525	18,2670
% variance	0,142	0,137	0,088	0,083	0,081	0,074	0,072	0,677

Coefficients des scores de facteur

Variable	Facteur1	Facteur2	Facteur3	Facteur4	Facteur5	Facteur6	Facteur7
PEU1	0,158	0,042	0,048	0,105	0,197	0,176	-0,488
PEU2	-0,070	0,039	-0,305	0,124	0,007	0,012	-0,039
PEU3	0,054	-0,001	0,087	-0,010	-0,461	0,107	0,129
PEU4	-0,002	0,074	0,060	0,095	-0,501	0,133	0,081
PE1	0,032	-0,048	0,062	-0,093	0,129	-0,328	-0,070
PE2	0,025	-0,010	0,030	0,002	-0,032	-0,259	0,159
PE3	0,124	-0,008	0,059	0,046	0,015	-0,211	-0,015
PE4	-0,090	-0,013	0,031	0,051	0,058	-0,505	0,000
PU1	0,266	-0,004	0,015	0,027	-0,006	0,140	0,005
PU2	0,278	-0,040	0,035	0,019	0,009	0,107	-0,004
PU3	0,272	0,020	0,004	0,037	-0,012	0,186	-0,003
PU4	0,263	-0,029	0,084	0,005	0,059	0,029	-0,093
SP1	-0,018	0,246	0,118	-0,001	0,063	-0,047	-0,104
SP2	0,009	0,235	0,113	0,027	-0,035	0,059	-0,162
SP3	-0,027	0,234	-0,057	0,059	0,036	0,011	0,086
SP4	-0,017	0,278	0,043	0,016	-0,074	0,078	0,058
SP5	-0,021	0,250	0,011	0,025	-0,111	0,059	0,105
PS1	-0,056	-0,089	-0,440	-0,002	0,067	-0,028	0,146
PS2	-0,035	-0,063	-0,449	0,032	0,106	0,029	0,013
PS3	-0,018	-0,018	-0,132	0,063	0,040	-0,129	-0,051
PS4	0,085	-0,024	-0,255	-0,064	0,041	0,306	-0,072
PPR1	-0,071	0,033	-0,089	0,388	0,008	-0,130	0,080
PPR2	0,128	0,064	0,066	0,406	0,029	0,099	-0,156
PPR3	0,011	-0,022	-0,101	0,380	-0,088	0,015	0,012
I1	-0,029	-0,000	0,091	-0,052	-0,185	-0,091	-0,163
I2	-0,116	-0,036	-0,020	-0,040	-0,077	-0,104	-0,302
I3	-0,101	-0,031	-0,037	-0,038	-0,071	-0,077	-0,256

Our construct here contains 27 items with 7 dimensions. We performed a factorial analysis, and we needed to delete 2 items due to their commonalities lower than 0.5 (namely PS3 with 0.289 and PS4 with 0.443). Furthermore, we also drop 6 items due to their factor lower than 0.6 (PEU1, PEU2, PE1, PE2, PE3 and I1). We then decide to start again the factorial analysis without those items.

PART 2

Saturations de facteurs et communalités avec rotations

Rotation varimax

Variable	Facteur1	Facteur2	Facteur3	Facteur4	Facteur5	Facteur6	Facteur7	Communalité
PEU3	-0,094	-0,246	0,134	-0,104	-0,844	-0,098	-0,085	0,827
PEU4	0,064	-0,073	-0,039	-0,223	-0,875	-0,077	-0,061	0,836
PE4	0,187	-0,265	-0,010	-0,049	-0,168	-0,215	-0,835	0,879
PU1	0,108	-0,797	0,074	0,043	-0,114	-0,189	-0,064	0,707
PU2	0,006	-0,840	0,059	0,024	-0,075	-0,080	-0,073	0,727
PU3	0,180	-0,757	0,085	0,076	-0,156	-0,184	0,067	0,681
PU4	0,055	-0,837	0,098	-0,112	-0,013	-0,042	-0,208	0,772
SP1	0,797	-0,035	0,150	-0,024	0,116	0,057	-0,276	0,752
SP2	0,687	-0,047	0,134	-0,205	-0,016	0,051	-0,272	0,611
SP3	0,851	-0,092	0,021	0,112	0,088	-0,247	0,008	0,815
SP4	0,899	-0,066	0,141	0,056	-0,061	-0,109	0,073	0,856
SP5	0,849	-0,151	0,095	0,000	-0,105	-0,170	0,090	0,801
PS1	0,126	-0,221	0,164	-0,013	-0,139	-0,848	-0,105	0,842
PS2	0,201	-0,257	0,107	-0,239	-0,051	-0,786	-0,105	0,807
PPR1	-0,057	0,217	-0,820	0,147	0,091	0,027	-0,022	0,754
PPR2	-0,113	0,015	-0,793	0,043	0,121	0,265	0,023	0,729
PPR3	-0,251	0,058	-0,806	-0,037	-0,111	-0,001	0,020	0,731
I2	-0,019	0,068	0,077	-0,875	-0,198	-0,100	-0,102	0,836
I3	0,021	-0,026	0,051	-0,908	-0,110	-0,077	0,037	0,848
Variance	3,5920	2,9602	2,1131	1,8149	1,6947	1,6723	0,9635	14,8108
% variance	0,189	0,156	0,111	0,096	0,089	0,088	0,051	0,780

Coefficients des scores de facteur

Variable	Facteur1	Facteur2	Facteur3	Facteur4	Facteur5	Facteur6	Facteur7
PEU3	-0,026	0,020	0,050	0,118	-0,560	0,069	-0,004
PEU4	0,060	0,079	-0,059	0,041	-0,593	0,069	0,042
PE4	-0,052	0,067	-0,018	0,093	-0,008	-0,023	-0,942
PU1	-0,011	-0,303	-0,036	0,013	0,025	0,013	0,073
PU2	-0,037	-0,350	-0,028	-0,018	0,057	0,098	0,048
PU3	0,031	-0,295	-0,040	0,030	-0,032	0,010	0,237
PU4	-0,036	-0,350	-0,009	-0,107	0,136	0,155	-0,109
SP1	0,225	0,029	0,021	-0,023	0,071	0,165	-0,264
SP2	0,200	0,022	0,007	-0,114	0,017	0,178	-0,238
SP3	0,255	0,018	-0,096	0,050	0,036	-0,118	0,125
SP4	0,291	0,019	-0,028	0,035	-0,089	0,025	0,207
SP5	0,276	-0,016	-0,066	0,001	-0,092	-0,014	0,252
PS1	-0,074	0,093	-0,008	0,096	0,019	-0,618	-0,008
PS2	-0,036	0,033	-0,060	-0,085	0,125	-0,547	0,025
PPR1	0,062	0,042	-0,426	0,039	0,006	-0,115	-0,047
PPR2	0,066	-0,113	-0,408	-0,075	0,050	0,117	0,023
PPR3	0,007	-0,027	-0,429	-0,050	-0,077	-0,096	0,046
I2	-0,006	0,023	-0,017	-0,501	0,046	0,014	-0,019
I3	0,024	-0,062	-0,050	-0,571	0,116	0,034	0,171

Our new construct here contains 19 items with 7 dimensions. After starting the factorial analysis again, we can see that the commonalities are now good with all the commonalities higher than 0.5. Concerning the factors, they are all higher than 0.6 and attributed to 1 factor per dimension. Our scale is then represented by 19 items and 7 dimensions.

Cronbach's Alpha for Perceived Ease of Use

As we keep only one item for this variable, we don't need to perform a factorial analysis on it.

Cronbach's Alpha for Perceived Enjoyment

Alpha de Cronbach

Alpha
0,8227

Variance	2,2313	2,2313
% variance	0,744	0,744

The Cronbach's Alpha is higher than 0.7 (here it is 0.8825 for Perceived Enjoyment). This means that the 3 items of this dimension measure a unidimensional construct: the Social Presence.

The cumulative percentage variance is 70.4%.

Cronbach's Alpha for Perceived Usefulness

Alpha de Cronbach

Alpha
0,8538

Variance	2,7897	2,7897
% variance	0,697	0,697

The Cronbach's Alpha is higher than 0.7 (here it is 0.8538 for Perceived Usefulness). This means that the 4 items of this dimension measure a unidimensional construct: the Perceived Usefulness.

The cumulative percentage variance is 69.7%.

Cronbach's Alpha for Social Presence

Alpha de Cronbach

Alpha
0,8825

Variance	3,5182	3,5182
% variance	0,704	0,704

The Cronbach's Alpha is higher than 0.7 (here it is 0.8825 for Social Presence). This means that the 5 items of this dimension measure a unidimensional construct: the Social Presence.

The cumulative percentage variance is 70.4%.

Cronbach's Alpha for Perceived Security

Alpha de Cronbach

Alpha
0,8094

Variance	1,6805	1,6805
% variance	0,840	0,840

The Cronbach's Alpha is higher than 0.7 (here it is 0.8094 for Perceived Security). This means that the 2 items of this dimension measure a unidimensional construct: the Perceived Security.

The cumulative percentage variance is 84%.

Cronbach's Alpha for Perceived Privacy Risk

Alpha de Cronbach

Alpha
0,7807

Variance	2,0871	2,0871
% variance	0,696	0,696

The Cronbach's Alpha is higher than 0.7 (here it is 0.7807 for Perceived Privacy Risk). This means that the 3 items of this dimension measure a unidimensional construct: the Perceived Privacy Risk.

The cumulative percentage variance is 69.6%.

Cronbach's Alpha for Interpretability

Alpha de Cronbach

Alpha
0,8243

Variance	1,7035	1,7035
% variance	0,852	0,852

The Cronbach's Alpha is higher than 0.7 (here it is 0.8243 for Interpretability). This means that the 2 items of this dimension measure a unidimensional construct: the Interpretability.

The cumulative percentage variance is 85.2%.

Appendix 6: Factorial Analysis for the construct Attraction towards AI

Alpha de Cronbach

Alpha
0,8583

Saturations de facteurs et communalités sans rotations

Variable	Facteur1	Communalité
AAI4	0,853	0,728
AAI5	0,849	0,721
AAI6	0,833	0,694
AAI7	0,816	0,666
Variance	2,8095	2,8095
% variance	0,702	0,702

Coefficients des scores de facteur

Variable	Facteur1
AAI4	0,304
AAI5	0,302
AAI6	0,297
AAI7	0,291

The construct corresponding to the respondents' Attraction towards AI products/services contains 7 items. We make a factorial analysis, and the results are presented just above. With the above results, we can notice that 3 items are lower than 0.6 (AAI1, AAI2 and AAI3). We then decide to delete these items and we start again the factorial analysis (the results are presented just above). As we can see, the commonalities are higher than 0.6. Also, we can note that the factors are higher than 0.6. Our scale is then represented by 4 items.

The Cronbach's Alpha is way higher than 0.7 (here it is 0.8583), so we can confirm that those 4 items measure well one and only one construct, the Attraction towards AI Product/Services of the users.

The cumulative percentage variance is 70.2%.

Appendix 7: Factorial Analysis for the construct AI Education

Alpha de Cronbach

Alpha
0,8650

Saturations de facteurs et communalités sans rotations

Variable	Facteur1	Communalité
AIE1	0,818	0,670
AIE2	0,816	0,665
AIE3	0,756	0,571
AIE4	0,826	0,682
AIE5	0,824	0,680
Variance	3,2677	3,2677
% variance	0,654	0,654

Coefficients des scores de facteur

Variable	Facteur1
AIE1	0,250
AIE2	0,250
AIE3	0,231
AIE4	0,253
AIE5	0,252

The construct corresponding to the respondents' AI Education contains 5 items. We make a factorial analysis, and the results are presented just above. With the above results, we can already notice that the commonalities are higher than 0.6 for each item (with the lowest one at 0.571). Also, we can note that the factors are higher than 0.6. We can therefore keep the 5 items, representing our scale by those 5 items.

The Cronbach's Alpha is way higher than 0.7 (here it is 0.8650), so we can confirm that those 5 items measure well one and only one construct, the AI Education of users.

The cumulative percentage variance is 65.4%.

Appendix 8: Descriptive Analysis

1) Gender Repartition

Lignes : gender

	Dénombrement	% de colonne	% du total
Femme	77	54,23	54,23
Homme	65	45,77	45,77
Total	142	100,00	100,00

2) Age Repartition

Lignes : age

	Dénombrement	% de colonne	% du total
18 ans ou moins	1	0,704	0,704
19-25	80	56,338	56,338
26-30	12	8,451	8,451
31-35	6	4,225	4,225
36-40	4	2,817	2,817
41-45	9	6,338	6,338
46-50	12	8,451	8,451
51-55	9	6,338	6,338
56-60	8	5,634	5,634
Plus de 60 ans	1	0,704	0,704
Total	142	100,000	100,000

3) Education level Repartition

Lignes : education_level

	Dénombrement	% de colonne	% du total
Autre...	2	1,41	1,41
Doctorat	3	2,11	2,11
Secondaire inférieur	3	2,11	2,11
Secondaire supérieur	14	9,86	9,86
Supérieur non universitaire	39	27,46	27,46
Universitaire	81	57,04	57,04
Total	142	100,00	100,00

4) Profession Repartition

Lignes : profession

	Dénombrement	% de colonne	% du total
Autre...	4	2,817	2,817
Cadre	19	13,380	13,380
Chercheur d'emploi	12	8,451	8,451
Employé.e	41	28,873	28,873
Etudiant.e	51	35,915	35,915
Indépendant.e	6	4,225	4,225
Ouvrier(ère)	2	1,408	1,408
Pensionné.e	2	1,408	1,408
Personne au foyer	2	1,408	1,408
Profession libérale	3	2,113	2,113
Total	142	100,000	100,000

5) Revenue Repartition

Lignes : revenue

	Dénombrement	% de colonne	% du total
Entre 1000 et 1499 €	6	4,23	4,23
Entre 1500 et 1999 €	18	12,68	12,68
Entre 2000 et 2499 €	26	18,31	18,31
Entre 2500 et 2999 €	7	4,93	4,93
Entre 3000 et 3499 €	7	4,93	4,93
Moins de 999 €	57	40,14	40,14
Plus de 3500 €	21	14,79	14,79
Total	142	100,00	100,00

6) Frequency Repartition

Lignes : frequency

	Dénombrement	% de colonne	% du total
Plus de 3 fois par jour	79	55,634	55,634
Une fois par jour	28	19,718	19,718
2 à 3 fois par semaine	11	7,746	7,746
Une fois par semaine	13	9,155	9,155
Une fois tous les 2 mois	7	4,930	4,930
Une fois par an	1	0,704	0,704
Moins d'une fois par an	1	0,704	0,704
Presque jamais	2	1,408	1,408
Total	142	100,000	100,000

7) Money Spent Repartition

Lignes : money_spent

	Dénombrement	% de colonne	% du total
0 €	40	28,169	28,169
Entre 0,01 et 0,99 €	2	1,408	1,408
Entre 1 et 4,99 €	7	4,930	4,930
Entre 10 et 19,99 €	15	10,563	10,563
Entre 20 et 29,99 €	15	10,563	10,563
Entre 30 et 39,99 €	3	2,113	2,113
Entre 40 et 49,99 €	5	3,521	3,521
Entre 5 et 9,99 €	12	8,451	8,451
Entre 50 et 59,99 €	2	1,408	1,408
Entre 60 et 69,99 €	3	2,113	2,113
Entre 90 et 99,99 €	1	0,704	0,704
Je ne sais pas	30	21,127	21,127
Plus de 100 €	7	4,930	4,930
Total	142	100,000	100,000

Appendix 9: Moderating Variables

Transparency – Users' Trust in AI Products/Services

Moderating Variable: Age

La procédure GLM

Variable dépendante : Trust

Source	DDL	Somme des carrés	Carré moyen	Valeur F	Pr > F
Modèle	3	27.9515098	9.3171699	5.09	0.0023
Erreur	138	252.8530676	1.8322686		
Total sommes corrigées	141	280.8045775			

R-carré	Coef de var	Racine MSE	Trust Moyenne
0.099541	31.38173	1.353613	4.313380

Source	DDL	Type I SS	Carré moyen	Valeur F	Pr > F
Perceived_transparen	1	26.35492972	26.35492972	14.38	0.0002
age_cat	1	0.08419003	0.08419003	0.05	0.8306
Inter_TrustAge	1	1.51239009	1.51239009	0.83	0.3652

Source	DDL	Type III SS	Carré moyen	Valeur F	Pr > F
Perceived_transparen	1	18.09289081	18.09289081	9.87	0.0021
age_cat	1	1.58040327	1.58040327	0.86	0.3547
Inter_TrustAge	1	1.51239009	1.51239009	0.83	0.3652

Paramètre	Estimation	Erreur type	Valeur du test t	Pr > |t|
Constante	2.582020043	0.59302995	4.35	<.0001
Perceived_transparen	0.437547320	0.13924051	3.14	0.0021
age_cat	0.135629179	0.14603728	0.93	0.3547
Inter_TrustAge	-0.034162314	0.03760191	-0.91	0.3652

La procédure REG
Modèle : MODEL1
Variable dépendante : Trust

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	27.67301	9.22434	5.03	0.0024
Erreur	138	253.13157	1.83429		
Total sommes corrigées	141	280.80458			

Root MSE	1.35436	R carré	0.0985
Moyenne dépendante	4.31338	R car. ajust.	0.0790
Coeff Var	31.39900		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	3.18846	0.50423	6.32	<.0001	0
Perceived_transparency	1	0.31201	0.13449	2.32	0.0218	0.28312
age_less_25	1	-0.47169	0.73981	-0.64	0.5248	-0.16604
Inter_TransparencyAgeLess	1	0.07828	0.18398	0.43	0.6712	0.12476

La procédure REG
Modèle : MODEL1
Variable dépendante : Trust

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	27.67301	9.22434	5.03	0.0024
Erreur	138	253.13157	1.83429		
Total sommes corrigées	141	280.80458			

Root MSE	1.35436	R carré	0.0985
Moyenne dépendante	4.31338	R car. ajust.	0.0790
Coeff Var	31.39900		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	2.71677	0.54136	5.02	<.0001	0
Perceived_transparency	1	0.39029	0.12555	3.11	0.0023	0.35416
age_more_25	1	0.47169	0.73981	0.64	0.5248	0.16604
Inter_TransparencyAgeMore	1	-0.07828	0.18398	-0.43	0.6712	-0.10781

Moderating Variable: Gender

La procédure GLM

Variable dépendante : Trust

Source	DDL	Somme des carrés	Carré moyen	Valeur F	Pr > F
Modèle	3	27.5070966	9.1690322	5.00	0.0026
Erreur	138	253.2974808	1.8354890		
Total sommes corrigées	141	280.8045775			

R-carré	Coef de var	Racine MSE	Trust Moyenne
0.097958	31.40929	1.354802	4.313380

Source	DDL	Type I SS	Carré moyen	Valeur F	Pr > F
Perceived_transparen	1	26.35492972	26.35492972	14.36	0.0002
gender_cat	1	1.13684516	1.13684516	0.62	0.4326
Inter_TrustGender	1	0.01532175	0.01532175	0.01	0.9273

Source	DDL	Type III SS	Carré moyen	Valeur F	Pr > F
Perceived_transparen	1	11.86553923	11.86553923	6.46	0.0121
gender_cat	1	0.20310689	0.20310689	0.11	0.7399
Inter_TrustGender	1	0.01532175	0.01532175	0.01	0.9273

Paramètre	Estimation	Erreur type	Valeur du test t	Pr > |t|
Constante	2.913656081	0.52700862	5.53	<.0001
Perceived_transparen	0.340167179	0.13379028	2.54	0.0121
gender_cat	0.244046911	0.73364655	0.33	0.7399
Inter_TrustGender	-0.016442662	0.17996741	-0.09	0.9273

La procédure REG
Modèle : MODEL1
Variable dépendante : Trust

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	27.50710	9.16903	5.00	0.0026
Erreur	138	253.29748	1.83549		
Total sommes corrigées	141	280.80458			

Root MSE	1.35480	R carré	0.0980
Moyenne dépendante	4.31338	R car. ajust.	0.0783
Coeff Var	31.40929		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	2.91366	0.52701	5.53	<.0001	0
Perceived_transparency	1	0.34017	0.13379	2.54	0.0121	0.30868
gender_man	1	0.24405	0.73365	0.33	0.7399	0.08646
Inter_TransparencyMan	1	-0.01644	0.17997	-0.09	0.9273	-0.02581

La procédure REG
Modèle : MODEL1
Variable dépendante : Trust

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	27.50710	9.16903	5.00	0.0026
Erreur	138	253.29748	1.83549		
Total sommes corrigées	141	280.80458			

Root MSE	1.35480	R carré	0.0980
Moyenne dépendante	4.31338	R car. ajust.	0.0783
Coeff Var	31.40929		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	3.15770	0.51039	6.19	<.0001	0
Perceived_transparency	1	0.32372	0.12037	2.69	0.0080	0.29375
gender_woman	1	-0.24405	0.73365	-0.33	0.7399	-0.08646
Inter_TransparencyWoman	1	0.01644	0.17997	0.09	0.9273	0.02409

Moderating Variable: AI Education

La procédure GLM

Variable dépendante : Trust

Source	DDL	Somme des carrés	Carré moyen	Valeur F	Pr > F
Modèle	3	29.3321459	9.7773820	5.37	0.0016
Erreur	138	251.4724315	1.8222640		
Total sommes corrigées	141	280.8045775			

R-carré	Coef de var	Racine MSE	Trust Moyenne
0.104458	31.29593	1.349913	4.313380

Source	DDL	Type I SS	Carré moyen	Valeur F	Pr > F
Perceived_transparen	1	26.35492972	26.35492972	14.46	0.0002
AI_education	1	2.97659760	2.97659760	1.63	0.2034
Inter_TrustAIEducati	1	0.00061860	0.00061860	0.00	0.9853

Source	DDL	Type III SS	Carré moyen	Valeur F	Pr > F
Perceived_transparen	1	1.71748468	1.71748468	0.94	0.3333
AI_education	1	0.36159010	0.36159010	0.20	0.6567
Inter_TrustAIEducati	1	0.00061860	0.00061860	0.00	0.9853

Paramètre	Estimation	Erreur type	Valeur du test t	Pr > |t|
Constante	2.649172075	1.15472181	2.29	0.0233
Perceived_transparen	0.295215501	0.30408736	0.97	0.3333
AI_education	0.109553580	0.24593705	0.45	0.6567
Inter_TrustAIEducati	0.001124104	0.06101076	0.02	0.9853

Moderating Variable: Profession

La procédure GLM

Variable dépendante : Trust

Source	DDL	Somme des carrés	Carré moyen	Valeur F	Pr > F
Modèle	3	29.2436092	9.7478697	5.35	0.0016
Erreur	138	251.5609683	1.8229056		
Total sommes corrigées	141	280.8045775			

R-carré	Coef de var	Racine MSE	Trust Moyenne
0.104142	31.30144	1.350150	4.313380

Source	DDL	Type I SS	Carré moyen	Valeur F	Pr > F
Perceived_transparen	1	26.35492972	26.35492972	14.46	0.0002
profession_cat	1	0.30394186	0.30394186	0.17	0.6837
Inter_TrustProfessio	1	2.58473762	2.58473762	1.42	0.2358

Source	DDL	Type III SS	Carré moyen	Valeur F	Pr > F
Perceived_transparen	1	4.72318394	4.72318394	2.59	0.1098
profession_cat	1	1.81027822	1.81027822	0.99	0.3207
Inter_TrustProfessio	1	2.58473762	2.58473762	1.42	0.2358

Paramètre	Estimation	Erreur type	Valeur du test t	Pr > |t|
Constante	3.451695762	0.54045487	6.39	<.0001
Perceived_transparen	0.214816483	0.13345420	1.61	0.1098
profession_cat	-0.143796805	0.14429745	-1.00	0.3207
Inter_TrustProfessio	0.038454630	0.03229405	1.19	0.2358

Moderating Variable: Education Level

La procédure GLM

Variable dépendante : Trust

Source	DDL	Somme des carrés	Carré moyen	Valeur F	Pr > F
Modèle	3	26.5805380	8.8601793	4.81	0.0032
Erreur	138	254.2240394	1.8422032		
Total sommes corrigées	141	280.8045775			

R-carré	Coef de var	Racine MSE	Trust Moyenne
0.094658	31.46669	1.357278	4.313380

Source	DDL	Type I SS	Carré moyen	Valeur F	Pr > F
Perceived_transparen	1	26.35492972	26.35492972	14.31	0.0002
education_level_cat	1	0.06607458	0.06607458	0.04	0.8501
Inter_TrustEducation	1	0.15953372	0.15953372	0.09	0.7690

Source	DDL	Type III SS	Carré moyen	Valeur F	Pr > F
Perceived_transparen	1	0.69619074	0.69619074	0.38	0.5397
education_level_cat	1	0.20939003	0.20939003	0.11	0.7365
Inter_TrustEducation	1	0.15953372	0.15953372	0.09	0.7690

Paramètre	Estimation	Erreur type	Valeur du test t	Pr > |t|
Constante	3.560659706	1.68654098	2.11	0.0366
Perceived_transparen	0.230064522	0.37424352	0.61	0.5397
education_level_cat	-0.155151003	0.46019866	-0.34	0.7365
Inter_TrustEducation	0.029930595	0.10170864	0.29	0.7690

Moderating Variable: Revenue

La procédure REG
Modèle : MODEL1
Variable dépendante : Trust

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	32.55212	10.85071	6.03	0.0007
Erreur	138	248.25246	1.79893		
Total sommes corrigées	141	280.80458			

Root MSE	1.34124	R carré	0.1159
Moyenne dépendante	4.31338	R car. ajust.	0.0967
Coeff Var	31.09492		

Paramètres estimés					
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|
Intercept	1	2.32249	0.54043	4.30	<.0001
Perceived_transparency	1	0.46983	0.12821	3.66	0.0004
revenue_cat	1	0.28272	0.17508	1.61	0.1086
Inter_TranspRevenue	1	-0.05499	0.04321	-1.27	0.2054

Users' Trust in AI Products/Services – Intention to Use AI Products/Services

Moderating Variable: Attraction towards AI

La procédure GLM

Variable dépendante : Intention_to_use

Source	DDL	Somme des carrés	Carré moyen	Valeur F	Pr > F
Modèle	3	38.3287058	12.7762353	9.58	<.0001
Erreur	138	183.9592441	1.3330380		
Total sommes corrigées	141	222.2879499			

R-carré	Coef de var	Racine MSE	Intention_to_use Moyenne
0.172428	20.56221	1.154573	5.615023

Source	DDL	Type I SS	Carré moyen	Valeur F	Pr > F
Trust	1	9.61643607	9.61643607	7.21	0.0081
Attraction_towards_A	1	28.66644686	28.66644686	21.50	<.0001
Inter_TrustAttractio	1	0.04582289	0.04582289	0.03	0.8532

Source	DDL	Type III SS	Carré moyen	Valeur F	Pr > F
Trust	1	1.52892304	1.52892304	1.15	0.2861
Attraction_towards_A	1	1.66609851	1.66609851	1.25	0.2655
Inter_TrustAttractio	1	0.04582289	0.04582289	0.03	0.8532

Paramètre	Estimation	Erreur type	Valeur du test t	Pr > |t|
Constante	5.790498884	0.80219303	7.22	<.0001
Trust	0.188213866	0.17574382	1.07	0.2861
Attraction_towards_A	-0.261616499	0.23401088	-1.12	0.2655
Inter_TrustAttractio	-0.009746016	0.05256627	-0.19	0.8532

Moderating Variable: AI Education

La procédure GLM

Variable dépendante : Intention_to_use

Source	DDL	Somme des carrés	Carré moyen	Valeur F	Pr > F
Modèle	3	35.7999548	11.9333183	8.83	<.0001
Erreur	138	186.4879951	1.3513623		
Total sommes corrigées	141	222.2879499			

R-carré	Coef de var	Racine MSE	Intention_to_use Moyenne
0.161052	20.70305	1.162481	5.615023

Source	DDL	Type I SS	Carré moyen	Valeur F	Pr > F
Trust	1	9.61643607	9.61643607	7.12	0.0086
AI_education	1	22.73989436	22.73989436	16.83	<.0001
Inter_TrustAIEducati	1	3.44362436	3.44362436	2.55	0.1127

Source	DDL	Type III SS	Carré moyen	Valeur F	Pr > F
Trust	1	5.59311035	5.59311035	4.14	0.0438
AI_education	1	11.07981997	11.07981997	8.20	0.0048
Inter_TrustAIEducati	1	3.44362436	3.44362436	2.55	0.1127

Paramètre	Estimation	Erreur type	Valeur du test t	Pr > |t|
Constante	2.100895523	1.06847463	1.97	0.0513
Trust	0.526441870	0.25876744	2.03	0.0438
AI_education	0.642893725	0.22452191	2.86	0.0048
Inter_TrustAIEducati	-0.084301789	0.05280983	-1.60	0.1127

Moderating Variable: Profession

La procédure GLM

Variable dépendante : Intention_to_use

Source	DDL	Somme des carrés	Carré moyen	Valeur F	Pr > F
Modèle	3	38.6005080	12.8668360	9.67	<.0001
Erreur	138	183.6874419	1.3310684		
Total sommes corrigées	141	222.2879499			

R-carré	Coef de var	Racine MSE	Intention_to_use Moyenne
0.173651	20.54701	1.153719	5.615023

Source	DDL	Type I SS	Carré moyen	Valeur F	Pr > F
Trust	1	9.61643607	9.61643607	7.22	0.0081
profession_cat	1	17.41084856	17.41084856	13.08	0.0004
Inter_TrustProfessio	1	11.57322339	11.57322339	8.69	0.0037

Source	DDL	Type III SS	Carré moyen	Valeur F	Pr > F
Trust	1	0.00005000	0.00005000	0.00	0.9951
profession_cat	1	20.74797536	20.74797536	15.59	0.0001
Inter_TrustProfessio	1	11.57322339	11.57322339	8.69	0.0037

Paramètre	Estimation	Erreur type	Valeur du test t	Pr > |t|
Constante	5.968553441	0.44113451	13.53	<.0001
Trust	0.000597938	0.09755991	0.01	0.9951
profession_cat	-0.486890926	0.12332298	-3.95	0.0001
Inter_TrustProfessio	0.076255278	0.02586086	2.95	0.0037

La procédure REG
Modèle : MODEL1
Variable dépendante : Intention_to_use

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	20.24062	6.74687	4.61	0.0042
Erreur	138	202.04733	1.46411		
Total sommes corrigées	141	222.28795			

Root MSE	1.21000	R carré	0.0911
Moyenne dépendante	5.61502	R car. ajust.	0.0713
Coeff Var	21.54941		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	5.11573	0.36417	14.05	<.0001	0
Trust	1	0.13642	0.08086	1.69	0.0938	0.15333
profession_nojob	1	-1.83877	0.84558	-2.17	0.0314	-0.50033
Inter_TrustNoProfession	1	0.26522	0.17998	1.47	0.1429	0.34600

La procédure REG
Modèle : MODEL1
Variable dépendante : Intention_to_use

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	32.95312	10.98437	8.01	<.0001
Erreur	138	189.33483	1.37199		
Total sommes corrigées	141	222.28795			

Root MSE	1.17132	R carré	0.1482
Moyenne dépendante	5.61502	R car. ajust.	0.1297
Coeff Var	20.86047		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	3.85507	0.39815	9.68	<.0001	0
Trust	1	0.36488	0.08682	4.20	<.0001	0.41010
profession_student	1	2.59188	0.65954	3.93	0.0001	0.99385
Inter_TrustStudent	1	-0.49076	0.14668	-3.35	0.0011	-0.85943

La procédure REG
Modèle : MODEL1
Variable dépendante : Intention_to_use

Nb d'observations lues	142
Nb d'obs. utilisées	141
Nombre d'observations avec valeurs manquantes	1

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	16.85881	5.61960	3.75	0.0125
Erreur	137	205.04820	1.49670		
Total sommes corrigées	140	221.90701			

Root MSE	1.22340	R carré	0.0760
Moyenne dépendante	5.61939	R car. ajust.	0.0557
Coeff Var	21.77103		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	5.43266	0.44664	12.16	<.0001	0
Trust	1	0.06069	0.09913	0.61	0.5414	0.06792
profession_job	1	-1.41593	0.66782	-2.12	0.0358	-0.56421
Inter_TrustProfession	1	0.29222	0.14755	1.98	0.0496	0.55178

Moderating Variable: Education Level

La procédure GLM

Variable dépendante : Intention_to_use

Source	DDL	Somme des carrés	Carré moyen	Valeur F	Pr > F
Modèle	3	11.3160373	3.7720124	2.47	0.0647
Erreur	138	210.9719127	1.5287820		
Total sommes corrigées	141	222.2879499			

R-carré	Coef de var	Racine MSE	Intention_to_use Moyenne
0.050907	22.02020	1.236439	5.615023

Source	DDL	Type I SS	Carré moyen	Valeur F	Pr > F
Trust	1	9.61643607	9.61643607	6.29	0.0133
education_level_cat	1	1.50878269	1.50878269	0.99	0.3222
Inter_TrustEducation	1	0.19081851	0.19081851	0.12	0.7244

Source	DDL	Type III SS	Carré moyen	Valeur F	Pr > F
Trust	1	0.00790601	0.00790601	0.01	0.9428
education_level_cat	1	0.01485404	0.01485404	0.01	0.9216
Inter_TrustEducation	1	0.19081851	0.19081851	0.12	0.7244

Paramètre	Estimation	Erreur type	Valeur du test t	Pr > |t|
Constante	5.020195138	1.90745116	2.63	0.0095
Trust	0.031990706	0.44485429	0.07	0.9428
education_level_cat	-0.049788870	0.50510622	-0.10	0.9216
Inter_TrustEducation	0.041767208	0.11822191	0.35	0.7244

Moderating Variable: Revenue

La procédure GLM

Variable dépendante : Intention_to_use

Source	DDL	Somme des carrés	Carré moyen	Valeur F	Pr > F
Modèle	3	14.1412989	4.7137663	3.13	0.0279
Erreur	138	208.1466510	1.5083091		
Total sommes corrigées	141	222.2879499			

R-carré	Coef de var	Racine MSE	Intention_to_use Moyenne
0.063617	21.87226	1.228132	5.615023

Source	DDL	Type I SS	Carré moyen	Valeur F	Pr > F
Trust	1	9.61643607	9.61643607	6.38	0.0127
revenue_cat	1	0.04643647	0.04643647	0.03	0.8610
Inter_TrustRevenue	1	4.47842634	4.47842634	2.97	0.0871

Source	DDL	Type III SS	Carré moyen	Valeur F	Pr > F
Trust	1	0.65342530	0.65342530	0.43	0.5115
revenue_cat	1	3.86255055	3.86255055	2.56	0.1118
Inter_TrustRevenue	1	4.47842634	4.47842634	2.97	0.0871

Paramètre	Estimation	Erreur type	Valeur du test t	Pr > |t|
Constante	5.316129017	0.45364444	11.72	<.0001
Trust	0.066116047	0.10045096	0.66	0.5115
revenue_cat	-0.262729767	0.16417891	-1.60	0.1118
Inter_TrustRevenue	0.060968414	0.03538240	1.72	0.0871

La procédure REG
Modèle : MODEL1
Variable dépendante : Intention_to_use

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	20.96712	6.98904	4.79	0.0033
Erreur	138	201.32083	1.45885		
Total sommes corrigées	141	222.28795			

Root MSE	1.20783	R carré	0.0943
Moyenne dépendante	5.61502	R car. ajust.	0.0746
Coeff Var	21.51064		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	3.96112	0.45654	8.68	<.0001	0
Trust	1	0.35006	0.10038	3.49	0.0007	0.39345
revenue_low	1	1.76015	0.65424	2.69	0.0080	0.69893
Inter_TransRevenueLow	1	-0.33562	0.14427	-2.33	0.0215	-0.62758

La procédure REG
Modèle : MODEL1
Variable dépendante : Intention_to_use

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	27.16626	9.05542	6.40	0.0004
Erreur	138	195.12169	1.41393		
Total sommes corrigées	141	222.28795			

Root MSE	1.18909	R carré	0.1222
Moyenne dépendante	5.61502	R car. ajust.	0.1031
Coeff Var	21.17686		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	5.61268	0.41179	13.63	<.0001	0
Trust	1	0.05202	0.08884	0.59	0.5591	0.05847
revenue_medium	1	-1.93234	0.66393	-2.91	0.0042	-0.74095
Inter_TransRevenueMedium	1	0.31838	0.14895	2.14	0.0343	0.54681

La procédure REG
Modèle : MODEL1
Variable dépendante : Intention_to_use

Nb d'observations lues	142
Nb d'obs. utilisées	142

Analyse de variance					
Source	DDL	Somme des carrés	Moyenne quadratique	Valeur F	Pr > F
Modèle	3	12.51613	4.17204	2.74	0.0455
Erreur	138	209.77182	1.52009		
Total sommes corrigées	141	222.28795			

Root MSE	1.23292	R carré	0.0563
Moyenne dépendante	5.61502	R car. ajust.	0.0358
Coeff Var	21.95748		

Paramètres estimés						
Variable	DDL	Valeur estimée des paramètres	Erreur type	Valeur du test t	Pr > |t|	Valeur estimée normalisée
Intercept	1	4.79248	0.35748	13.41	<.0001	0
Trust	1	0.17429	0.08035	2.17	0.0318	0.19589
revenue_high	1	0.50179	1.02446	0.49	0.6250	0.15957
Inter_TransRevenueHigh	1	-0.03018	0.21259	-0.14	0.8873	-0.04716